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The Impact of COVID-19 on Bank Liquidity: An Analysis of the Basel III Liquidity Ratios in European Banks

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Abstract

The COVID pandemic in 2020 had a great impact on the European economy and the overall banking system. Banks had to react to the increased market uncertainty by adjusting their risk management. This thesis investigates how European banks adjusted their liquidity holdings in this context. Using data from the years 2015 to 2023 from a sample of banks supervised by the European Central Bank, this thesis analyses trends, structural breaks, and key drivers of liquidity changes. The, with Basel III implemented ratios, Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR) are used to determine the liquidity. For the analysis, the thesis splits the collected data into three phases, a pre-, during, and after-COVID phase and compares the banks' liquidity positions over time. The results of the thesis proves that the banks increased their liquidity buffers during the pandemic. It also explains the influence of bank size, stability, economic conditions, and profitability on the two liquidity ratios. The findings show that larger banks were slightly better positioned to maintain high liquidity ratios. By delivering these results, the thesis contributes to the ongoing research on financial stability, liquidity management, and regulatory effectiveness.

Zusammenfassung

Die COVID-19 Pandemie im Jahr 2020 hatte erhebliche Auswirkungen auf die europäische Wirtschaft und das gesamte Bankensystem. Banken reagierten auf die gestiegene Unsicherheit im Markt und definierten ihr Risikomanagement neu. In diesem Zusammenhang untersucht diese Master-Arbeit, wie europäische Banken aufgrund dessen ihre Liquiditätsreserven verändert haben. Mithilfe von Daten aus den Jahren 2015 bis 2023 analysiert die Arbeit Trends, Strukturbrüche und Einflussfaktoren für Veränderungen der Liquidität von Banken, die unter der Aufsicht der Europäischen Zentralbank stehen. Zur Bestimmung der Liquidität nutzt die Analyse die Basel III Kennzahlen; die Liquidity Coverage Ratio (LCR) und Net Stable Funding Ratio (NSFR).

Für die Untersuchung wird der Datensatz in drei Phasen aufgeteilt. Eine Pre-COVID Phase, eine Während-COVID Phase, sowie eine Post-COVID Phase. Auf diese Weise soll die Entwicklung der Liquiditätspositionen der Banken im Zeitverlauf verglichen werden. Die Ergebnisse der Arbeit zeigen, dass Banken während der Pandemie ihre Liquiditätspuffer erhöht haben. Zudem wird der Einfluss von Bankgröße, Stabilität, wirtschaftlichen Rahmenbedingungen und Rentabilität auf die Liquiditätskennzahlen analysiert.

Die Erkenntnisse zeigen, dass größere Banken, zumindest leicht, besser in der Lage waren, hohe Liquiditätsquoten aufrechtzuerhalten. Mit diesen Ergebnissen leistet die Arbeit einen Beitrag zur aktuellen Forschung über Finanzstabilität, Liquiditätsmanagement und die Wirksamkeit regulatorischer Maßnahmen.

1 Introduction

1.1 Introduction to the topic of the Thesis

Economic and financial crises appeared several times in the last century. Examples are the great depression in 1929, the oil crisis in 1973, the financial crises in 2008, and the COVID pandemic starting in 2020. All these crises had various effects on the overall economy, which were widely analyzed in financial and economic research, for example by Carmen M. Reinhart and Kenneth S. Rogoff, 2009. The banking sector is a central part of the economy and, therefore, is particularly vulnerable during those times of crisis. In the research, the question arises of how exactly such crises impact the banking sector. Recent papers, for example, a study by Schularick et. al, focus on this question. By analyzing the balance sheets of several thousand banks over more than a hundred years, they show that the behaviour of large banks changes before and after crises. (Matthwe Baron and Moritz Schularick, 2023)

The capital requirements and the liquidity demand in the market change during such crises; this was part of the research in various papers, for example, by Allen N. Berger and Christa H.S. Bouwman, 2017 or Jose M. Berrospide, 2012 and goes back to the findings of Diamond, D. W., & Dybvig, P. H., 1983, who explained the interplay between liquidity demand and the risk of bank runs. It seems that in the crises, which were analyzed in the research, the liquidity of the banks changed, which was also proved for the financial crises of 2008 (Berrospide, 2012).

To prevent or at least to weaken these effects on the liquidity in future crises, regulators introduced stricter liquidity requirements with the introduction of Basel III, including the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR), which were both designed to ensure that banks maintain enough liquidity to withstand a crisis (Basel Committee on Banking Supervision, 2010). The first large crisis after the introduction of those liquidity rules was the COVID pandemic, which began in 2020 and caused one of the most severe economic disruptions in recent history. Because of lockdowns, businesses faced a massive increase in financial distress, and the market became more volatile. The question arises of how banks have behaved during this pandemic and whether they have followed the same pattern as in the research mentioned above and adjusted their liquidity.

The current literature is very limited on this question; only a few recent papers have been found that focus on this topic. For example, a 2023 published study by Dung Viet Tran *et al.*, 2023. Therefore, this thesis shall build on the findings and investigate how banks' liquidity positions changed due to COVID. As the countries in the world had different strategies for handling the crises, it is essential to understand, in a first step, how the banking system of comparable countries was affected. The thesis, therefore, focuses on the European market, particularly on the system under the supervision of the European Central Bank. Following this idea, the thesis will focus on the following two research questions:

How have the liquidity positions of European banks, measured by the Basel III liquidity ratios (LCR and NSFR), changed during the COVID-19 pandemic? Did the LCR and NSFR change significantly because of COVID-19?
How do factors such as the stability of the bank, bank size, economic conditions, and profitability influence LCR and NSFR?

The decision to measure the liquidity using the two ratios is based on their regulatory background, which delivers reliable information about short-term and long-term liquidity. Additionally, since they are standardised and publicly reported, they provide a consistent and accurate basis for an analysis. This thesis analyses data from European banks between 2015 and 2023 to answer the research questions. This period guarantees the correctness of the ratios as they were introduced starting in 2015, and it also includes the years before, during, and after the pandemic, which allows a reliable comparison of the liquidity holdings.
Understanding how liquidity positions changed during the pandemic will help to understand banks' behaviour during crises even more. This thesis contributes to the ongoing research on the financial stability of the banking sector and the effects of the COVID pandemic.

1.2 Structure of the thesis

Following the structure of a financial research paper, the thesis provides a clear and detailed analysis of how the liquidity ratios of European banks developed because of uncertainty in the market caused by the COVID pandemic.

After the first chapter introduces the topic and motive behind the analysis, the second chapter focuses on the background of the liquidity management in the banking sector. Continuing, the thesis describes the evolution of banking regulations as the main focus of the thesis. Starting with Basel I and Basel 2 and further with Basel 3, where the liquidity ratios were introduced, on which the thesis is focused. The two ratios, the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR) are explained in detail, including their purpose, calculation, and regulatory implications. Additionally, this chapter briefly describes how the COVID pandemic has influenced the economy.

The third chapter presents a review of the existing literature. It focuses not only on literature with the same focus as this thesis but also on research on Basel regulations, liquidity management in the banking sector, and the impact of economic downturns on the banking sector.

The fourth chapter focuses on the methodology used for the thesis analysis. It describes how the data collection was conducted and why the sample was chosen. It also explains the sources of the financial data, such as annual reports and regulatory disclosures. Finally, the chapter gives insights into the key parameters used in the analysis, explains why these parameters were chosen, and describes the statistical methods used.

The fifth chapter is the central part of the thesis. It presents the results of the analysis. The chapter describes the exact approach, starting by testing the sample for a reliable result. Then, it explains the changes of the LCR and the NSFR caused by COVID and identifies trends in the different phases of the pandemic. Finally, the results of regression models are explained to describe the key drivers of the liquidity changes, which were proven before.

The final chapter summarizes all findings and compares the different results for both ratios to conclude the thesis. The chapter evaluates whether the Basel III liquidity ratios have changed because of COVID and which factors have influenced these changes.

Further figures, tables, and explanations are found in the Appendix, which will help understand the topic overall. To simplify readability, the COVID-19 pandemic is referred to simply as COVID in the following.

2 Background of the liquidity management in the banking sector

2.1 Understanding Regulatory Frameworks

2.1.1 Liquidity Definitions

Liquidity Risk

As analyzing the liquidity risk in the banking sector is part of this thesis, it is essential to understand its definition. Already Diamond, D. W., & Dybvig, P. H., 1983 included in their paper about bank runs, the role of liquidity risk and how it arises. According to the FED, liquidity risk is the risk that a bank cannot meet its contractual obligations on time, whether caused by actual or perceived reasons. (Board of Governors of the Federal Reserve System, 2023) Liquidity risk increases when a bank is not able to pay its obligations without high costs or by damaging its reputation. This can be caused by sudden events, like too many customers withdrawing money at once, which can lead to a bank run like Diamond & Dybvig described. If the trust in the banks' assets is decreasing, even though they are safe, this issue can increase even more. It is essential to clarify that risk differs from insolvency, where the value of liabilities exceeds assets. Liquidity risk describes the difficulty of quickly turning assets into cash without losses. Factors like fire sale prices and mismatches in asset and liability maturities, which were shortly described in the previous part, can increase this risk. Still, they are not always necessary for it to occur (Greenbaum, Stuart I. & Thakor, Anjan V. & Boot, Arnoud, 2015, pp. 121–122). Liquidity risk is one of the most dangerous risks in the banking sector. Because of the maturity transformation role of banks, the risk of being impacted by roll-over risks and withdrawals of deposits is very high, which can lead to funding gaps. (Greenbaum, Stuart I. & Thakor, Anjan V. & Boot, Arnoud, 2015, p. 127)

Liquidity Shock

A liquidity shock is an unexpected demand for liquidity from a single institution or a whole market (aktien-prognose.com, no date) It can arise from various reasons. As stated by Kolm, J, Laux, C & Lóránth, G, 2018 reasons include payment issues, employee strikes, or regulatory decisions. Beside the general definition of liquidity shock, it is interesting to understand the economic shock caused by COVID. According to Lorie K. Logan, 2021 the pandemic led to an extraordinary external shock, creating uncertainty that disrupted global economic activities. Incentives to control the pandemic increased concerns about the stability of the financial market and triggered a so-called “dash for cash" (see 3.2). Market participants changed their investments to safer and more liquid ones, which caused an increased volatility. Additionally, the supply of liquidity decreased as firms that typically provide loans decided to increase their cash reserves to cover potential future payment obligations. This resulted in an extraordinary increase in demand for liquidity. (Lorie K. Logan, 2021)

2.1.2 General idea of regulatory framework for banks

The intention to implement regulatory frameworks for banks emerged in 1974 due to the breakdown of the bank “Bankhaus Herstatt KGaA,” which led to the formation of the Basel Committee on Banking Supervision (BCBS) in 1975 (Mourlon-Druol, 2015). The failure of the Herstatt Bank showed the inconsistency between a self-regulating market and the demand for regulators.

BSBS published the first accord, Basel I in 1988, intending to introduce minimum capital requirements for banks. The upcoming chapter will define the details and calculation approach for Basel I.

2.1.3 Basel I – International Convergence of Capital Measurement and Capital Standards

As mentioned before, the first accord, the so-called Basel I, was published in 1988 by the BSBS under the name “International Convergence of Capital Measurement and Capital Standards.” (*International convergance of capital measurment and capital standards* 1988) The publication defines the constituents of capital, risk weights, a target standard ratio, and transitional and implementing arrangements.

The committee especially sees the equity of banks as a critical element for the safety of the banking system. In the first part of the accords, the constituents of capital define the equity capital as follows: “Issued and fully paid ordinary shares/common stock and non-cumulative perpetual preferred stock (but excluding cumulative preferred stock).” (*International convergence of capital measurement and capital* *standards* 1988) The first part can be defined as Tier 1 capital and the second as Tier 2 capital. It further defined five different risk weights, which should be kept simple (0%, 10%, 20%, 50%, and 100%), to group the bank assets into different categories. Each asset class is thereby categorized by one of the risk classes. Starting with the lowest risk class with 0% and 10% for cash, central bank, and government debt, going to 20% class for non-OECD public sector debt, increasing to 50% risk class for residential mortgages and 100% for debt belonging to the private sector. (*International convergence of capital measurement and capital standards* 1988) The target standard ratio is defined as the rate of capital a bank must maintain on the risk-weighted assets described above. The committee has set this rate to 8%, of which a minimum of half has to be covered by core capital, tier 1, and the other half is allowed to be covered by supplementary capital, tier 2.

Taking the three parts together, the capital requirements can, therefore, be described by the formula:

$$\frac{Capital}{Risk\ Weighted\ Assets} \geq 8\%$$

This formula is defined as the solvency ratio of liabilities to total assets. (*International convergence of capital measurement and capital standards* 1988) This formula can be described as the central part of the Basel 1 accords. Besides the ratio, the committee also suggested agreements to implement this ratio so that banks had a transitional period with an increasing ratio. Since it became clear over time that the regulations set out in Basel II were insufficient, new rules were defined under Basel II. (*International convergence of capital measurement and capital standards* 1988)

2.1.4 Basel II –A Revised Framework

In 2004, the BSBS published new accords - Basel 2—to address the need for advanced risk regulation. The information in the following paragraph is taken from the (*International Convergence of Capital Measurement and Capital Standards* 2004) The primary adjustment of Basel 2 was the introduction of a three-pillar approach, which will be explained shortly.

Basel 1's approach used fixed percentages based on the different categories in which the debtors were classified. There was no differentiation within these categories, addressing the varying levels of risk. This classification was replaced by the concept of risk-weighted assets (RWA) and the adjustment of the capital adequate ratio. Different categories of assets were assigned specific risk weights based on credit risk, market risk, and operational risk. (*International Convergence of Capital Measurement and Capital Standards* 2004)

The risk-weighted assets are determined by applying risk weights to the various asset classes to calculate the credit risk. These weights depend on the quality of the assets. The quality can be determined either through a standardized approach, by external ratings, or through the internal rating models of the banks themselves. The internal models require banks to estimate parameters like the probability of default (PD), loss-given default (LGD), and exposure at default (EAD). (Basel Committee on Banking Supervision, 2003, pp. 38–41)

Banks can also use external rating agencies to evaluate the assets as an alternative to internal risk modelling. Agencies like S&P, Moody's, and Fitch are used to assign credit grade obligations, which are then mapped to default probabilities. The definitions of Pillar 2 and Pillar 3 can be found in Appendix C - Explanation.

2.1.5 Basel III – A global regulatory framework for more resilient banks

The idea of this thesis is based on the liquidity regulations that were introduced with the Basel 3 Accords in December 2010. Therefore, it is crucial to look at the overall idea of Basel 3 and the adjustments to Basel 2 that were implemented. This includes the new liquidity requirements, which will be explained in the following chapters, and further regulatory standards for capital and banking supervision. The changes introduced by the Basel 3 Accords are documented in the official publication by the Basel Committee on Banking Supervision. (*Basel III: A global regulatory framework for more resilient banks and banking systems* 2010)

The financial crisis in 2007/2008 was one of the main reasons for introducing the new Basel 3 Accords as it became clear that the current version lacked control of the systemic risk in the banking sector. A 2011 published working paper by George Copiere studies the detailed reasons. (Georg, 2011) The study classifies systemic risk as the potential collapse of the entire financial system due to connections between separate financial institutions. If one institution or bank fails, it can cause others to fail, too. This effect leads to widespread problems. The different ratios explained and tested in this thesis shall reduce the systemic risk in several ways. Banks, which are very important to the system and so-called systemically important financial institutions, are especially forced to hold more capital. For this reason, the thesis focuses on a sample of banks under the supervision of the ECB to deliver valuable results. The liquidity standards, which will be tested in a regression model, shall prevent situations where banks can't pay their debts, which again could lead to a crisis. (Georg, 2011)

The transparency rules shall force banks to provide more information about their risks, which helps investors and other banks understand the risks better. This can reduce panic during tough, difficult times. The option to adjust capital requirements based on the economic situation can help to build up extra capital during good times, which helps during bad times. Basel III aims to make the financial system safer by using different rules and ratios. (Georg, 2011)

2.2 Regulatory Liquidity Requirements in Banks

Liquidity requirements in general and especially the Basel III liquidity requirements shall make banks more resilient to financial stress scenarios by ensuring they can manage their liquidity more effectively and have a sufficient high buffer. (Basel Committee on Banking Supervision, 2010, p. 3) The introduced rules, which will be explained below, aim to prevent liquidity crises, protect the economy, and maintain stability in the financial system.

2.2.1 Liquidity coverage ratio (LCR)

Idea and formula

As described in the previous chapter, the liquidity coverage ratio (LCR) is one of the main pillars of Basel 3, which aims to reduce the sector's riskiness. The overall concept was formulated in the Basel 3 accords. (*Basel III: A global regulatory framework for more resilient banks and banking systems* 2010) The idea of the LCR is to introduce a ratio that addresses short-term liquidity risk defined by high-quality liquid assets (HQLA), which are tested in a 30-day prolonged stress testing scenario. The concrete formula is defined as follows:

$$LCR = \left(\frac{HQLA}{Stress\ Test\ Over\ 30\ Days}\right) * 100$$

The exact definition of HQLA, which includes cash, central bank reserves, government bonds, and other assets, will be defined in the following paragraph. The definition and implementation of the stress test will also be defined in the following paragraphs. (*Basel III: A global regulatory framework for more resilient banks and banking systems* 2010)

The primary goal of the LCR is to introduce short-term resilience of banks' liquidity risk positions. The ratio should help banks have sufficient high HQLA to meet their liquidity needs during a stress period without relying on external support from other institutions like the central bank or other commercial banks. The ratio therefore works against the Lender of the Last resort principles, which is the focus of various studies in a recent paper by Chao Huang and Fernando Moreira, 2024, who analyzed the interaction between LCR, interbank rate, and the central bank's role as a lender of last resort and found that implementing non-optimal rules for calculating HQLA can decrease banks' capital ratios when liquidity rules are stringent.

The ratio shall enhance the banking sector's ability to absorb liquidity shocks, reduce the risk of financial instability, and help regulators with standardized metrics to measure liquidity. The LCR has to be reported to the regulators, for example, the European Central Bank ECB, regularly, where failures in the reporting may lead to regulatory sanctions, as stated in official publications of the European Union (European Parliament, 2014). The data scope that will be defined for the analysis in this thesis, therefore, focuses on banks that are under the supervision of the ECB to ensure that the collected data is meaningful and profound.

High-Quality Liquid Assets (HQLA)

As this study tries to understand how the overall stability of the banks and the banking system affects the LCR, it is essential to have a view on the definition and research on HQLA to understand how HQLA can be interpreted differently and, therefore, have a different impact on the ratio.

According to the Basel Committee on Banking Supervision (*LCR Liquidity Coverage Ratio LCR30 High-quality liquid assets* 2019) HQLA are characterized as follows. They must be quickly and easily convertible to cash with little to no loss in value. Also, they have to generate cash through sales or repos, even under stressful market conditions. If they fail the test for stressful market conditions and only generate cash with significant discounts, they are considered to have a lower quality level. Also, banks should be able to use HQLA to get cash directly from the central banks. In the accords, they differentiate between level 1 and level 2 class assets, whereby the overall stock of HQLA can only be filled with up to 40% of level 2 assets, with additional differentiation into 2A and 2B Level assets. The overall HQLA stock is then calculated using the equation of the different levels, including a reduction as an adjustment for the percentage cap. While Level 1 assets are not subject to any haircut, Level 2 assets are subject to a 15% haircut. (*LCR Liquidity Coverage Ratio LCR30 High-quality liquid assets* 2019)

Cech classifies Level 1 assets as debt securities insured on a sufficiently high legal framework. (Christian Cech, 2022, p. 262) (e.g., covered bonds, structured bank debt securities) and which hold the highest credit rating, ECAI 1. (Highest level of rating by external credit assessment institutions like the common rating agencies) (European Bank Authority, no date). Furthermore, Cech explains Level 2A assets as claims against other public entities, which are covered bonds of lower credit quality (ECAI 2) and smaller volume as well as corporate bonds of the highest credit quality. (ECAI 1) Level 2B assets include covered bonds and corporate bonds of lower credit quality as well as stocks. (Christian Cech, 2022, pp. 262–263)

HQLA is part of the current research investigating how banks lay out the abovementioned rules. A 2017 published study by Patrella and Resti classifies HQLA and evaluates their true liquidity in contrast to the expected liquidity by the given regulations. In their paper, they try to find out if domestic treasury bonds, if they are classified as highly liquid, fulfill the liquidity requirements and can be defined as trusted. (Giovanni Petrella and Andrea Resti, 2017)

Their results show that treasury bonds significantly drop in liquidity during stressed markets, even if they are classified as HQLA. This effect limits their effectiveness in increasing bank stability. They explain this fact by saying that central bank channels for liquidity are not always assured. Additionally, the interplay between market conditions and bond-specific factors leads to higher risk despite being classified as HQLA. (Giovanni Petrella and Andrea Resti, 2017). Their results might help explain the reasons in the following analysis why the connection between the LCR and the bank's stability is not given in any case.

Further studies, such as a recent paper by Gong and Wei, search for reasons why banks might choose assets with less quality instead of high-quality assets, despite the idea of regulatory rules. They create a model that includes the financial structure of banks, including asset quality, and tries to explain banks' decisions on the asset and liability side. They find that under certain conditions, banks prefer lower quality assets financed by short-term debt over higher quality assets due to lower equity costs and higher rollover risks. According to the authors, this stands in contrast with socially optimal strategies, where banks invest in high-quality assets financed using long-term debt and equity. Overall, their model suggests that implementing liquidity regulations brings together the private incentives of banks with social welfare. They argue that regulations on HQLA increase financial stability. (Yaxian Gong and Xu Wei, 2022) Results like those suggested by Gong and Wei have to be taken into account when testing whether the liquidity ratios lead to increased stability.

Stress-Testing

Next to the HQLA, the second important part of the liquidity ratio is the introduced stress test scenario, which has to hold cash outflows over 30 days as stated in the accords. (*Liquidity Coverage Ratio LCR40 Cash inflows and outflows* 2019) According to Bologna and Segura, the idea of conducting stress tests had already been developed in the 1980s. It came up as a risk management tool to evaluate the resilience of assets and portfolios against various conditions. (Bologna and Segura, 2017) During the financial crisis (2007-2009) the idea of stress testing was further developed into an important regulatory tool and therefore became a part of the Basel III framework. (Bologna and Segura, 2017) Stress tests shall evaluate the impact of a predefined scenario on the financial positions of a bank. (Carl Olsson, 2022, p. 378) According to Olsson, it consists of three parts. First, the scenario determination must be created, which has to be plausible and oriented to reflect historic worst-case events. Second is an evaluation process where output values under normal and stress situations are defined. Third, an impact assessment, which compares the different values. Lastly, the production of financial values describes the impact on the banks' balance sheet and profitability. (Carl Olsson, 2022, p. 378) The idea in the Basel III accords is to ensure that banks hold enough capital to withstand economic shocks. It measures the difference between the total net cash outflows and inflows over a 30-day stress scenario. Outflows are estimated by calculating how much of a bank’s liabilities, like deposits or loans, are expected to be withdrawn. Inflows on the other side are calculated based on how much inflow the bank expects to receive within these 30 days, but they can only count to 75% of the total outflows. (*Basel III: The Liquidity Coverage Ratio and liquidity risk monitoring tools* 2013)

2.2.2 Net stable funding ratio (NSFR)

While the LCR was introduced to handle liquidity issues in the short term, the Net Stable Funding Ratio (NSFR) focuses more on creating long-term stability. To handle this, the NSFR is settled on the liability side of the balance sheet. (Carl Olsson, 2022, pp. 230–235). Similar to the LCR, the NSFR is defined as a ratio that has to be fulfilled with over 100%. The equation is defined by the Available Stable Funding (ASF) ratio determined by the required stable funding (RSF), which will be explained in the following paragraph.

The formula can be written as follows:

$$NSFR = \frac{Available\ stable\ funding}{Required\ stable\ funding}\ x\ 100\% \geq 1$$

The general idea of the NSFR is to prevent mismatches in the maturities of assets and liabilities and to reduce the dependence on short-term financing transactions. (Christian Cech, 2022, p. 73) As described by Cech, the NSFR is calculated based on liabilities, assets, and off-balance sheet items. It is noted that items cannot be part of more than one category of required stable funding and are part of the category with the most excellent required financing. The calculation of the NSFR has to be done on a single and consolidated basis. For banks classified as smaller and less complex, a simplified NSFR can be calculated, including consolidated reporting categories and maturity bands. Due to the weighting factors, the simplified NSFR is stricter than the standard NSFR. (Christian Cech, 2022, p. 74) This thesis focuses on large banks that are under the supervision of the European Central Banks to avoid a mismatch between the standard and the simplified NSFR. By this it can be ensured that the analysis delivers comparable results.

Banks not fulfilling the requirements must try to reach 100% again. If they do not satisfy this requirement, the responsible authorities are allowed to undertake appropriate measures, which are not clearly defined. The latest literature has already examined how the ratio can be achieved. A paper by Michael King investigates in his paper from 2013, cost-effective strategies to reach the target of 100%. (Michael R. King, 2013) In his analysis, he collects data from banks located in fifteen different countries below the threshold. Based on the assumption that the most effective possibilities to reach the ratio are to increase high liquid assets ranked highly and extend the maturity of the funding in the wholesale area, he studies the tradeoff between the regulation, risk and profitability. The results are valuable for this thesis as

they show that there are synergies between NSFR and the LCR. (Michael R. King, 2013)
He proves that reaching the ratio will increase the holding of more liquid assets and contribute to achieving the LCR. Is the analysis part of the thesis, both ratios will be investigated separately, but based on the results like from Michael King, the overall result will be evaluated combined.
Furthermore, the estimation of the NSFR for banks in different countries shows that out of fifteen countries in sum, the banks of ten of the countries do not meet the required threshold by the end of 2019. The analysis in this thesis, which includes non-estimated data starting from 2015, will show different results after implementing the rules. The number of banks with a ratio below the threshold is reduced to a minimum. This result shows that only through the notice banks have anticipated the rules and ratios from 2009 to 2015.
Additional papers, like a 2017 published study by Cuong Ly et al., look at the NSFR from another side. They try to explain if there are connections between the adjustments, frictions, and the systemic risk. (Kim Cuong Ly *et al.*, 2017) A study by Iftekhar et al. tries to prove that if banks adjust the NSFR quicker to reach the required threshold faster, it can reduce the systemic risk and contribute to a more stable financial system. They show this behavior by comparing banks with equal NSFR levels but different adjustment speed. According to their results, the probability of a liquidity shortfall for banks is quickly reduced, and therefore, the systemic risk is reduced. (Iftekhar Hasan, Suk-Joong Kim and Eliza Wu, 2015) Interesting for this thesis is especially the outcome that for smaller banks these effects are stronger. During this thesis's regression analysis, a control variable for the size of the banks will be included to explain the impact.
To understand the NSFR more in detail in Appendix C - ExplanationTwo paragraphs explain the available stable funding and the required stable funding in detail.

2.3 Liquidity Hoarding

As this thesis investigates the liquidity increase during COVID, it is essential to understand which reasons can lead to such an increase in liquidity or hoarding of liquidity. A study by Gale et al. separates liquidity hoarding for two different reasons. It can occur due to precautionary or because of speculative motives. The precautionary motive arises from the risk of future liquidity shocks. Banks want to retain cash to avoid the high costs of providing liquidity later. On the other hand, the speculative lets banks hold cash to profit from future market distress, like buying assets cheaply when the liquidity demand is high and prices fall. Expectations of asset-price changes drive the two motives and might create liquidity shortages, inefficiencies, and market instability. (Douglas M. Gale and Tanju Yorulmazer, 2011, pp. 292–293)

A study by Berrospide defines banks as liquidity hoarders if their ratio of total liquid assets to total assets increased by more than three percentage points because of the crises. (Jose M. Berrospide, 2012, p. 11) This definition cannot be used entirely for this thesis, as this thesis looks at given liquidity ratios. Still, the percentage points can be used as a reference value to determine if banks reacted similarly during the COVID crisis. Various research studies focus on the reasons for liquidity hoarding. A publication by Alberto Ramos, 1996 explains that banks hoard increased cash to self-insure for further cash demands and to signal to the market that their solvency is not at risk. Also, he investigated this based on previous crises, it might be seen during COVID again.

2.4 Influence of COVID on the European Banking Sector

2.4.1 Economic sentiment indicator

The indicator of economic sentiment is a monthly survey conducted within the industry, the consumer retail and construction industry, which shall show the expectations of these in the future development of economic growth. (Oesterreichische Nationalbank, no date) It is scaled to 100 on a long-term mean. As described in previous chapters, an increase in liquidity holdings in banks can be caused by uncertainty in the markets; therefore, comparing the results of the analyses with the exceptions in the market could help to find explainable reasons. The indicator, Appendix (Figure 7 - Economic sentiment indicator (Statistisches Bundesamt, **2023**) shows a clear decrease starting in 2020 in parallel to the beginning of the COVID pandemic. It fell from 105.2 in February 2020 to 58.7 in April 2020. Afterwards, an increase is visible. According to Statistisches Bundesamt, 2023 This is the sharpest decrease since the beginning of the survey in 1985. In the results of the thesis, this will be used to explain the statistical breaks in the banks' liquidity holdings. As seen in paragraph 2.4.1, a reason for increased liquidity might be precautions taken by the banks, which were also affected by the uncertainty seen in the indicator's development.

The further development shows an increase back to the starting value and even higher up to a maximum of 117.8 in October 2021, at which the crisis was still in place, and a decrease afterwards, which might have different reasons. A similar course of development is seen in the liquidity holdings of the banks (6.5.1). The analyses of the reason for this development can be part of further research and would go beyond the scope of this thesis.

2.4.2 Historical Evidence from Crises

As the COVID pandemic is not the first crisis affecting the banking sector and their behaviour, it is essential to view comparable situations in the past and how they affected the liquidity holdings in the banking sector.

Going back to the 1920th and 1930th, American banks suffered illiquidity because of excessive real estate lending (Wicker, 1996, p. 16). Banks reacted the same way as assumed in this thesis, strengthening their liquidity positions. The demand for liquidity led to an increased selling of lower-quality bonds and attractiveness of government bonds as reserves. This again increased the prices of government bonds and lowered their yields, while the prices of lower-graded securities fell. The drop in bond values reduced the banks' portfolios' overall worth and their financial strength, leading to the banking crises and failures. (Friedman and Schwartz, 1963, p. 312) The analysis by Friedman and Schwartz must be considered while evaluating the results of the thesis study. Interesting for this thesis is especially the observation that banks increased the amounts of voluntary excess reserves during this time. (Jose M. Berrospide, 2012, p. 4) This situation might be comparable to the analysed development during COVID.

Despite the great depression, the financial crises of 2007 and 2008 and other crises, led to increased liquidity requirements. The consequences of that are described in the previous chapters and are part of the literature review. The historical similarities show that while each crisis has its own reasons and developments, the reactions of the banking sector can be compared. Understanding the adjustments of liquidity positions in previous crises might help to analyse the reasons for adjustments during the pandemic. The question that arises here is whether the Basel III regulatory frameworks for liquidity management increased the financial institutions' stability to withstand the crises' shocks better and protect the stability of the overall financial system.

2.4.3 Dash for Cash

During the beginning of the COVID crisis, a so-called “Dash for Cash” impacted the global financial markets and the banking sector. According to Robert Czech, Bernat Gual-Ricart, Joshua Lillis and Jack Worlidgefootnote[, 2021 the Covid dash for cash can be defined as a period with huge trading volumes on the market across all financial systems. A spontaneous increase in the liquidity demand from non-bank financial institutions drove this increased volume. In March 2021, these institutions sold bonds and equivalent assets at historically high levels, which dealers had to absorb. This resulted in a rapid demand for liquidity, and banks and dealers had to handle more trades of government bonds. The exact date of the dash for cash depends on the source but lies around the period from 9 to 23 March. (Robert Czech, Bernat Gual-Ricart, Joshua Lillis and Jack Worlidgefootnote[, 2021)

This phenomenon might explain the banks' increased liquidity holdings in the main phase of the crises. Nevertheless, the analysis of this paper looks at the yearly ratios of liquidity holdings. Therefore, it can not be analysed in detail.

3 Literature Review

Looking at the literature which focuses on the impact of the COVID pandemic on banks' liquidity holdings is very limited. Only a few papers can be found that directly investigate this topic. This may be because the pandemic was not far behind, so little research has been conducted in this area. At the same time, however, this also shows the necessity of analyzing this master's thesis.

Nevertheless, in the finance literature, several papers can be found that analyse aspects of the liquidity management of companies and banks. The literature has developed on implementing Basel III regulations, which explain the importance of the Liquidity Coverage Ratio and the Net Stable Funding Ratio in enhancing financial stability. This chapter provides an overview of studies focusing on these liquidity ratios' implementation implications and general liquidity management. As the thesis investigates the development of liquidity during the COVID pandemic, it additionally explores how the pandemic has influenced liquidity risk management practices.

This thesis should be given special importance to the literature that explains the impact of crises and similar economic situations on the liquidity in the market, especially on banks' liquidity. Literature in these areas is currently reduced, which again determines the importance of the study in this thesis. Nevertheless, some publications can be found. A study by Kocaarslan, 2023 Investigates the relationship between funding liquidity risk and the volatility of U.S. municipal green bonds during the COVID crisis. Also, this study does not focus directly on the behavior of banks; it tries to explain the impact of COVID on the liquidity market. A more closely to this thesis related study by Dung Viet Tran *et al.*, 2023 tries to explain bank liquidity hoarding during COVID in the United States. They run multivariate regression with dummy variables for COVID on a sample of banks. By this they can show that banks indeed hoard liquidity to resist the uncertainty. They also show that the increase in liquidity decreases the probability of default. Their results align with this thesis's assumptions, while this thesis focuses on the European market.

A study by Allen N. Berger *et al.*, 2022, also focuses on liquidity hoarding during uncertain economic times and shows similar results of increased liquidity under uncertainty. Evaluating Basel III under COVID, as done in this thesis, is also part of the study by Anani and Owusu, 2023. Their research focuses on whether the Basel II requirements improved banks against a shock like the COVID crisis. They found that banks that fulfilled the regulatory requirements pre-crises have a lower insolvency risk. The study does not focus on liquidity but has a comparable research focus. A study by Jose M. Berrospide, 2012 investigates the impact of financial crises on higher liquidity holding. His results suggest that the increased liquidity during the crises arises due to on-balance sheet risks. He also investigates the connection between bank size and increased liquidity holdings, which will also be part of the analysis of this thesis. According to the study, this effect is more substantial for smaller banks.

Besides studies that work on the impact of crises on liquidity, this thesis needs to look at literature that focuses on the Basel III accords. Several studies in the current research focus on the general effects of the liquidity ratios introduced by Basel III. Michael King (Michael R. King, 2013) For example, he explores in his study the bank's behavior to meet the NSFR requirement and finds out that the net interest margin is reduced because of an increase in better-rated securities.

Kim Cuong Ly *et al.*, 2017 Also, it looks specifically at the effects on the NSFR but in the context of systemic risk. They found out that the speed of the implementation impacts the system risk. In contrast, banks with faster adjustment speeds are better positioned to mitigate liquidity risk and stabilize the financial system. They also find differences within the size of the banks, which will also be investigated as a predictor in this thesis. (Kim Cuong Ly *et al.*, 2017). The idea goes along with a paper by Jobst, who investigates how the NSFR interacts with systemic liquidity risks and provides insights into banks' funding structures. (Andreas A. Jobst, 2014) A study by Wei et al. shows that the NSFR helps banks to rely less on short-term debt, reduce the risks, and make the system safer. They argue that the NSFR improves stability during times of crisis by ensuring that banks have stable funding but may slightly lower profits. Using their model, they explain that an increase in the NSFR also increases a bank's survival chances, which comes along with the assumption of this thesis of increased liquidity holdings because of COVID. (Xu Wei, Yaxian Gong and Ho-Mou Wu, 2017)

Even more literature, with a direct focus on the LCR, can be found, which will be used in this thesis as the second measurement of banks' liquidity and the set-up of highly qualified liquid assets. A recent study by Fuhrer, Müller and Steiner, 2017 focuses primarily on high-quality liquid assets and determines how the classification of these assets affects their value. Their results indicate the existence of an HQLA premium. Such a premium might lead to the increase in the promotion of HQLA because of the LCR.

The impact of liquidity regulations on assets is also part of further research. A study by Banerjee and Mio, 2018 focuses on how liquidity regulations influence the composition of assets and liabilities. They conclude that the banks' balance sheets do not increase while the size of high liquid assets increases significantly. This comes along with the assumption of this thesis that banks adjust their financial structure during a crisis. Also, Banerjee and Mio, 2018 do not focus directly on the Basel liquidity ratios, but on the Individual Liquidity Guidance; their results can be compared. Further studies also focus on regulatory requirements similar to those of the LCR. Clemens Bonner analyses the liquidity requirements in the Netherlands with a focus on the cost side and on corporate lending rates and found evidence that banks cannot pass increased funding costs to corporate clients and that regulation does not significantly affect corporate lending. (Clemens Bonner, 2012) This raises further questions on the hypothesis of the analysis in this thesis: why do banks increase liquidity holdings in uncertain economic times if it comes along with increased costs. Negative effects are investigated by Sundaresan and Xiao, 2024, who studied the effects of liquidity requirements on other bank functions and the whole banking system. They find evidence that the regulation led to the transfer of liquidity risks to institutions that are not forced to meet those requirements. Their results can be used to explain an overall increase in liquid assets in the analysed sample of this thesis. The results align with Roberts, Sarkar and Shachar, 2023 who investigated differences between LCR banks and banks that are not forced to fulfill the LCR.

As this thesis focuses on the regulatory liquidity requirements and the counterplay between liquidity and economic situation, it is essential to look at recent literature on these topics. A recently published study by Giorgia Simion *et al.*, 2024, focuses on the side effects of liquidity regulation of European banks. They find evidence that higher liquidity holdings lead to increased credit event expectations of creditors as they assume increasing bank default risk. This negative reaction to tighter regulation has been more registered for weaker than stronger banks. The analysed increase during the COVID in this thesis has to be evaluated under such results. Kjell G. Nyborg and Per Östberg, 2014 study the interaction of liquidity demands on the interbank markets and financial market activities. They test the liquidity pull-back hypothesis and identify relationships between uncertainty, stock liquidity, and trading activity. They show that pre-crisis banks hold significant amounts of securities, which serve as a liquidity buffer. This thesis focuses on the liquidity ratios and not their composition, so it does not stand in contrast to their results. (Roberts, Sarkar and Shachar, 2023) As this thesis aims to understand the influence of liquidity regulation on bank behavior (with a focus on a crisis), the study by Haan and van den End, 2013 is essential to include. They find evidence that banks reduce their liquidity buffers during crises due to central bank support. This stands opposite to this thesis's assumption and must be challenged. Haan and van den End, 2013 also explain that banks with more capital hold fewer liquid assets, which changes in crises. This, again, can be used as an explanation for the analysis in this thesis. Their results, which show that regulators should consider that banks often hold more liquid assets than required and plan beyond the one-month LCR rule, go along with the idea of this thesis.

Finally, it is also essential to study literature which does not directly focus on the banking sector but on the impact of COVID on the economy, in general, to get a better understanding of a study during COVID, published study by Christian Espinosa-Méndez and Jose Arias, 2021 looks at the stock exchange changes of different European countries and finds evidence for increased herding behavior in the capital markets. Herding behavior describes the situation where the collective behavior of the market influences investors and they act accordingly to other investors. This phenomenon could also be considered while analysing banks' similar behavior during the crises. Another study by Ralf Fendel, Frederik Neugebauer and Lilli Zimmermann, 2021 evaluates the impact of monetary and fiscal decisions of the European Central Bank and the European Commission during COVID. They found evidence that solvent countries like Germany were more affected by the decisions. Another recent paper by Marco Bernardini and Annalisa De Nicola, 2025, which was just released in 2025, looked at the effects of government bond purchases during the crisis. According to their results, purchasing long-term bonds reduced their interest rate by up to 5 basis points. Last, a study by Pierre Hítalo Nascimento Silva and Jevuks Matheus de Araújo, 2023 was looking at the uncertainty caused by COVID. They found evidence that COVID was indeed increasing uncertainty.

4 Data Collection and Research Methodology

4.1 Methodology

The thesis uses a structured approach with various steps to determine the changes in the liquidity ratios. The research combines a time series analysis, structural breakpoint tests, variance analysis, and panel regression models. The combination of different methodologies shall help to get a clear understanding of the changes in liquidity ratios over time and help to provide meaningful results.

A time series analysis will determine general trends in the two liquidity ratios between 2015 and 2023. This time series analysis shall help identify significant liquidity level changes, mainly because of COVID. Afterwards, a structural break analysis will be performed to determine such changes from a more data-based view. As a result of the structural break analysis, it cannot fully explain the changes in the next step, an analysis of the variance is used to test if differences between the LCR and the NSFR are across the different phases of COVID. The separation in a pre-, a during, and a post-COVID phase will be explained later. The variance analysis shall help test whether these changes are statistically significant and determine if the observed changes in liquidity ratios were due to real economic effects or caused by random fluctuations. To explain the differences between the phases, a Turkey HSD will be performed.

In the last step, a panel regression will be performed. The panel regression itself follows a step-by-step approach. This will be done by testing with a naive model, then by a time-fixed model, and lastly, a fully saturated model. The chosen approaches are also based on different statistical tests performed in advance. In these tests, the overall sample is checked for stationarity, multicollinearity, serial correlation, and heteroskedasticity to ensure the liability of the regression results. Also, based on the statistical tests, robust standard errors are applied to correct statistical issues.

4.2 Definition of the Sample

4.2.1 Source of the Sample

For the scope of the analysis, the list of supervised banks of the European Central Bank (ECB) was used, published, and regularly updated by the ECB via its online service. (European Central bank, 2024). The selected version is the list of supervised entities from the cut-off date on 01.09.2024, which contains a total of 113 banks under the supervision of the ECB.

The idea of choosing the published data of the ECB comes with the approach that the thesis aims to conduct a cross-country analysis to counteract possible deviations and peculiarities that occur country-specifically. Since banks that are as comparable as possible are selected in this sample, it makes sense to use countries and banks that are subject to the same central bank, the ECB. This ensures that the collected data and the analysis deliver relevant and sufficient results. Also, this eliminates the need to include other comparable markets and financial systems, such as the USA. In future studies of the ratios, the European financial market could alternatively be compared with another financial market. This is in line with current economic theory, for example, described in “Geld, Kredit und Banken: Eine Einführung” by Gischer et al., who explain in chapter 10.5 how banks of the same financial market share identical macroeconomic factors, regulatory frameworks, and central bank policies, where the banks share identical systemic influences like interest rates and economic cycles, by which the evaluation of the financial stability and bank performance is more comparable. (Gischer, Herz and Menkhoff, 2020, pp. 160–165)

4.2.2 Cleansing of the Sample

The overall sample of 113 banks was then examined using the procedures explained in the following sections. Parts of the banks were subsidiaries of banks that did not belong to the European Union. These banks were removed from the list to contain only entire European banks and kept in the form with the idea of the study. If their business is clearly separated, they were kept. Also, banks that significantly changed their business because of mergers and acquisitions were removed as the ratios and values changed way above average. Many of the banks remaining on the list did not publish the required data in the form that it was possible to collect for this thesis. Finally, 72 banks remain for which reliable data could be collected. Also, for these banks, collecting data for each year of the observation was impossible. In the analysis and test chapter, tests and adjustments will be performed because of the unbalanced sample. A detailed examination of the sample will be described in the following sections. The final list of the 72 banks, including the country and the year's observations, can be found in the appendix.(Table 13 - Banks, incl. observation years and country)

4.3 Data collection (2015-2023)

The required data was collected from mainly two sources. The annual reports of the banks and the pillar 3 disclosures. The approach to collect the data manually and directly in the reports was chosen because of a lack of available sources and also to follow the approach of having actual data and no estimated values.
There are different available sources which might have been chosen to collect the data, like S&P Capital IQ, which was generally available, but after further investigation, it did not fit the requirements as it could not deliver information about the two ratios (Liquidity coverage ratio and net stable funding ratio) in detail. Also, a significantly high number of banks which were selected in the original sample were not available.
The collection approach to get the required data was therefore chosen in the way to directly visit the Websites of the banks and to search manually in the published reports. The collected data was afterwards stored in a master list and standardized to enable an evaluation. The exact calculation of the individual variables is explained in the relevant sections below. In a few exceptions, data on individual ratios was also taken from publications by rating agencies or ratings from banks. The number of data collected in this way is limited to a non-significant minimum.
As explained in section 3.3, the main source of data collection was the annual reports of the single banks. Most of the selected banks in the sample directly publish the overview of the required ratios and balance sheet numbers in a central overview in their reports for a time horizon of two to three years. These numbers were taken if possible to reduce the data collection effort, and the review in the annual report of the mentioned years was skipped. Therefore, slight deviations in the figures may occur if the bank has corrected the results for the following year after publishing them. Whenever it was impossible to collect the two main ratios (LCR and NSFR) directly in the annual reports the numbers were taken from the Pillar 3 disclosure

requirements. Random samples were carried out between the yearly report and Pillar 3 publications to ensure that the published ratios match. This could be verified to ensure the consistency and correctness of the data.

4.4 Parameters

To ensure meaningful results, the following ratios and variables were collected from the sources above and used for the analysis afterwards. As the liquidity coverage ratio and net stable funding ratio are under primary investigation in this study, the defined background of the ratios and the detailed understanding have already been explained in section 2.2. They will therefore not be discussed further at this point.

4.4.1 Cost Income Ratio

As this thesis aims to understand the impact of the profitability measured by the cost income ratio on the banks' liquidity ratios, the cost income ratio is used as a predictor. According to Gischer, Herz and Menkhoff, 2020, p. 123 the cost income ratio is defined as the quotient of the administrative expenses (operating expenses) and the sum of interest and commission income (operation income).

$$CIR = \frac{Operating\ Expenses}{Operating\ Income}$$

The CIR was directly taken from the bank's annual reports, which are published based on the bank's calculations. Banks which did not publish the ratio were excluded from the sample as described in section 3.2.1. The accuracy of the data is assumed due to the banks' obligation to report truthfully.

As the thesis investigates, if stricter liquidity rules impact banks' efficiency, the ratios are expected to correlate positively. Gischer et. Al interprets the cost-income ratio percentage increase as the effort to be invested to keep the output constant. A lower cost-income ratio is, therefore, more efficient for a bank. Applying the cost-income ratio to evaluate efficiency is a common approach in the research. Beccalli et al., for example, use it in their paper “Efficiency and Stock Performance in European Banking” to investigate the efficiency of banks compared to the stock price. (Beccalli, Casu and Girardone, 2006).

4.4.2 GDP Growth

To measure the economic situation and country where the bank is officially located, the GDP Growth per country is used, as it represents the economic growth by measuring changes in gross domestic product over time, adjusted for inflation or deflation. (Caroline Banton, 2024). By this definition, it should help as a macroeconomic control variable to explain changes in a bank's liquidity positions for economic reasons. The data here was taken from the International Monetary Fund via their website to have reliable values. (International Monetary Fund, no date) The growth was afterwards filtered for the required years and added to the overall data collection. The values for all the necessary countries can be found in the appendix. (Table 13 - Banks, incl. observation years and country

. The data of the International Monetary Fund is assumed to be correct and valid as they apply standardized methods for calculating across all countries. For the panel regression, this should ensure comparability between the countries where the banks are located.

Choosing GDP growth rates as a measurement for the economic situation goes along with current literature where it is used as a macroeconomic control variable, for example, by Albertazzi and Gambacorta, 2009 who used GDP Growth as a parameter while describing bank profitability. Also, a recent study by Michael Ellington, Chris Florackis and Costas Milas, 2017 uses the GDP growth to explain liquidity in the asset market.

In the thesis's conclusion, the analysis's weaknesses and the parameters are addressed. A weakness of looking at the GDP growth rates per country is that banks conduct their business in various countries. Just looking at the country where the headquarters are stated might impact the overall results. This weakness in the thesis is acknowledged but accepted, as the negative impact is considered relatively minor.

4.4.3 Size of the bank

Bank size is a commonly used parameter in research literature because it significantly influences various financial and operational ratios and bank numbers. Larger banks often benefit from economies of scale and better access to the capital markets. (Beccalli, Elena, Anolli, Mario and Borello, Giuliana, 2015, p. 15) This can affect their liquidity ratios, profitability and stability. Based on these assumptions, this thesis will analyze whether the size of the bank affects the regulatory liquidity ratios.

According to Jan Schildbach, 2017 different options are available to measure the size of a bank. Primarily, they suggest taking the revenues, followed by equity capital, and then measuring the size using the total assets or the market cap. In this thesis, the total assets of the banks are collected. The total assets are not as highly impacted by the other control variables in the regression as, for example, the revenue would be. Here, the parameter cost-income ratio explained above could lead to Multicollinearity, which shall be avoided. The use of Equity capital is also not seen as effective as it reflects the book values and, by this, is stable. (Jan Schildbach, 2017, p. 1) This thesis focuses on a crisis, which might lead to unwanted results. Reason for deciding on total assets is that the data is available and the collection is simple.

Total assets might also have disadvantages if they were selected as a remaining variable. Disadvantages are, according to Jan Schildbach, 2017, pp. 6–7 Especially in the non-differentiation between high-risk and low-risk positions. This can be misleading. Also, the valuation of financial assets is challenging as many assets have no transparent market prices and rely on internal models and assumptions. These disadvantages must be considered while evaluating the results of the analyses.

For the analysis, the value of the total assets is not directly taken. Instead, the natural logarithm is calculated to create a more comparable database. This goes along with the current literature cited in this thesis before. (Jose M. Berrospide, 2012) (Banerjee and Mio, 2018) (Dung Viet Tran *et al.*, 2023) The natural logarithm in the thesis is mainly used to scale the significant values of the total assets and to make the analyses more robust to outliers. Also, it will improve the possibility of interpretations and open options for analysing relative changes.

4.4.4 Z_Score

The z-score will be used to measure the stability of the banks. The Z_score is a widely used measurement to define the stability of a bank. A higher Z_score indicates here a more stable bank and less overall risk. (Felix Noth, 2015, p. 26) In the current research literature, the Z-score is used in various papers, for example by Hakenes et al., 2014, who analyzed the effect of small banks on the economy and use the Z-score to measure their solvency. Berger, Klapper and Ariss, 2009 also use the indicator; details will be provided below. Also, the indicator is widely used. It is essential to mention that in the current research, the Z_score is viewed critically and with requirements for adjustments. For example, a recent paper by (Bilal Hafeez et al., 2022) develops a forward-looking z_Score to predict the insolvency risk of a bank ahead of time. A study by Laetitia Lepetit and Frank Strobel, 2015, on the other side, challenges the validity of the z_Score to measure banks' solvency and refine the standard z-Score by providing a tighter bound on the risk of insolvency by a one-sided inequality. Nevertheless, the standard is used. Further research might build on this and test the research questions with an enhanced version of the Z_Score.

For the definition of the z_score, this thesis follows the approach of Berger, Klapper and Ariss, 2009, p. 105, who define the Z_Score as follows:

$$Z_{Score} = \frac{ROA + \frac{E}{TA}}{\sigma(ROA)}$$

Where ROA is the return on assets for a bank per year, the return on assets are not taken directly from the annual reports of the banks, instead it is calculated manually, as the total assets were already collected as an independent parameter, the profit after tax was taken from the income statement of the banks. The calculation follows here the commonly used approach, for example, used by Will Kenton, 2023.

E represents the equity of the bank in the measured year. The equity value was also taken directly from the annual reports. TA represents the total assets. The ratio of equity and the total assets is known as the equity ratio, which measures the share of a company’s assets financed by equity instead of debt. The closer the ratio reaches 100%, it indicates a greater reliance on equity than loans. Consequently, this parameter can provide insight into the organisation’s long-term financial stability and is, therefore, part of the Z-Score. (Adam Hayes, 2022)

σ(ROA) describes the standard deviation of the bank’s return on assets over the given period. As for the sample used for analysis, the periods of the banks differ between three and nine years, and the calculation also varies between the banks. The calculation was done based on the collected data.

5 Results

5.1 Research Question

As mentioned in the thesis's introduction, the analysis focuses on two main research questions. The first and main question of the thesis shall investigate how the liquidity positions of European banks, measured by the Basel III liquidity ratios LCR and NSFR, changed during the COVID pandemic. It shall investigate if there are any significant differences in the LCR and NSFR levels of the European banks between the pre-COVID (2015–2019), during COVID (2020–2021), and post-COVID (2022–2023) phases.

The second research question focuses more on the impact of different parameters on the ratios. The question focuses on how key factors such as bank stability, size, economic conditions, profitability, and regulatory requirements impacted the liquidity holdings. This will be done by comparing the pre-COVID phase with a post-COVID phase. By this, the thesis investigates whether the relationships between these factors and the liquidity ratios shifted due to the crisis.

5.2 Statistical Tests

5.2.1 Stationarity

According to Horst Rottmann and Benjamin R. Auer, 2018 a stationary time series is given if the mean and variance are finite and do not change over time. In the context of a panel regression like the one performed in this thesis, it is crucial to fulfil stationarity to have valid and interpretable results. A commonly used way to test for stationarity is the Dickey-Fuller-Test. The test checks for the existence of a unit root, which would indicate non-stationarity. For the results, it can be said that the more negative the test statistic is, the stronger the evidence that the data is stationary. If the p-value is less than 0.05, the null hypothesis of a unit root will be rejected, confirming that the data is stationary and suitable for regression analysis. The Null-Hypothesis, therefore, indicates non-stationary, while the alternative hypothesis suggests stationarity. (Yugesh Verma, 2024)

In the context of this thesis, it is essential to conduct the test as the stationarity helps ensure that observed changes between the Pre- and post-COVID phase are caused by real economic effects and not just by statistical noise.
The results of the Dickey-Fuller-Test for the given sample show the following for LCR and NSFR.

$$\text{LCR}: \ \text{DickeyFuller} = -5.1792; \text{Lag Order} = 9; \ \text{pValue} = 0.01$$

$$\text{NSFR}: \ \text{DickeyFuller} = -5.3484; \text{Lag Order} = 9; \ \text{pValue} = 0.01$$

The Null-Hypothesis can be rejected because the p-Value for LCR is small enough. The test result was strongly negative, proving that LCR was stationary. For NSFR, the test outcome is even more negative while the p-Value stays the same; consequently, it also proves that NSFR is stationary.

5.2.2 Multicollinearity

Multicollinearity exists if two or more of the independent parameters in a regression model are correlated with each other. (The Pennsylvania State University, 2018) The existence makes it difficult to determine the individual effect of each of the parameters. It reduces the precision of the estimates and leads to inconsistent test results. Therefore, the accuracy and reliability of the regression analysis are limited. (The Pennsylvania State University, 2018) To avoid these effects, the independent variables used in this thesis are tested for multicollinearity. The test in this thesis is conducted by calculating Variance Inflation Factors (VIF). The results of the VIF show the degree of multicollinearity in a regression model and are calculated by the following formula:

$$VIF = \frac{1}{1 - R^2}$$

Where R-squared explains how strong a parameter is described by the other independent parameters in the model. A higher R leads to a higher VIF, indicating a higher risk of multicollinearity. A VIF of 1 means, on the other hand, suggests no multicollinearity. (Robert C. Kelly and Timothy Li, 2024) The calculation of the VIF for the used parameters in this thesis leads to the following results:

z_Score	ln_Size_EUR	GDP_growth	Cost_income_ratio
1.017232	1.017364	1.011427	1.012705

The calculation is valid for the NSFR and LCR regression. The results clearly indicate no multicollinearity between the parameters, as all values are slightly above the minimum of 1.

5.2.3 Serial Correlation

According to Caroline Banton, 2021 serial correlation is defined as the situation where the value of a parameter is influenced by its past values, which means that the observation shows a connection over time. This issue is common in time-series data, for example, in stock prices, as the current performance impacts the future stock price. In the case of serial correlation, the data follows a pattern instead of being distributed randomly. It, therefore, can affect the accuracy of predictions, like in the case of this master's thesis, the development of the LCR and NSFR before and after COVID. It is, therefore, crucial to detect and address serial correlation for a reliable data analysis. (Caroline Banton, 2021)
For the test of serial correlation in this thesis, the Breusch-Godfrey/Wooldridge test is used. As defined by Horst Rottmann, 2018aThe test checks for autocorrelation in a regression and compares the null hypothesis of no autocorrelation against the alternative that autocorrelation exists. The test is performed by using the residuals from the original model and then creating a regression on a constant. The test statistic follows a chi-squared distribution, and if it exceeds a critical value, the null hypothesis is rejected, indicating the presence of autocorrelation.
For the given sample and regression, the test results are given as follows:

LCR

Data: LCR ~ z_Score + ln_Size_EUR + GDP_growth + Cost_income_ratio
Chisq = 10.799, df = 1, p-value = 0.001016
Alternative hypothesis: serial correlation in idiosyncratic errors

The Chi-squared value is 10.799 with 1 degree of freedom and a p-value of 0.001016. As the p-value is significantly smaller than 0.05, the null hypothesis is rejected: no serial correlation exists. This indicates serial correlation.

NSFR

Data: NSFR ~ z_Score + ln_Size_EUR + GDP_growth + Cost_income_ratio

Chisq = 36.035, df = 1, p-value = 1.938e-09

Alternative hypothesis: serial correlation in idiosyncratic errors

The Chi-squared value is 36.035 with 1 degree of freedom and a p-value of 1.938e-09. As the p-value is significantly smaller than 0.05, the null hypothesis is rejected that there is no serial correlation. Means, serial correlation is existing.
As for LCR and NSFR, the test shows clear evidence of serial correlation, the model must be adjusted. The adjustment will be done by applying Driscoll-Kraay standard errors. Further explanations follow in chapter 5.3.1.

5.2.4 Hausman tests

The Hausman test compares fixed effects and random effects models to determine which is more sufficient for the analysis. The test compares the two estimation methods to check if they provide similar and reliable results. (Horst Rottmann, 2018b) The null hypothesis assumes that both estimators provide consistent results, but one is also efficient. If the alternative hypothesis is true, the first estimator becomes inconsistent, while the second remains reliable. Which means there is a significant difference between them. If the null hypothesis holds, the random effects model should be used; if rejected, a fixed effects model should be used. (Horst Rottmann, 2018b) For the given regressions in the analysis, the test leads to the following results:

LCR ~ z_Score + ln_Size_EUR + GDP_growth + Cost_income_ratio
chisq = 18.842, df = 4, p-value = 0.000844
Alternative hypothesis: one model is inconsistent

NSFR ~ z_Score + ln_Size_EUR + GDP_growth + Cost_income_ratio
chisq = 115.5, df = 4, p-value < 2.2e-16
alternative hypothesis: one model is inconsistent

The test results show that using a fixed effects model is the better choice for the regression analysis. For LCR, the test indicates that predictors are correlated with the dependent parameter. The value of 18.842 is relatively high, meaning a significant difference exists between the fixed and random effects models. As the p-value is very low, the fixed effects model is suggested. The effects are even more substantial for the NSFR, with a value of 115.5 and an even lower p-value for LCR. The test results indicate that the used predictors (bank stability, size, economic conditions, profitability) do not affect all banks equally. The use of a fixed effects model helps to produce more unbiased results. Therefore, the fixed model is applied in the further analysis of this thesis, and all further analysis and results are based on this.

5.2.5 Heteroscedasticity

Heteroskedasticity occurs in a regression analysis when the variance of the residuals varies across different values. This leads to an uneven distribution of the residuals. In some cases, this forms, for example, a cone shape in the residual plot. Heteroskedasticity is a problem in the analysis because standard regression methods, like the ones used in this thesis, assume that errors have the same spread. If the spread changes, the analysis results may not be reliable. (CFI Team, no date)
To test for heteroscedasticity, this thesis uses the Breusch-Pagan Test. The test checks if the volatility of errors in a regression model is constant, which is then defined as homoscedastic or not constant and therefore heteroskedastic. The test regresses the squared residuals from the original model on explanatory variables. The test statistic is calculated by multiplying the squared R of this regression by the sample size. It then follows a Chi-square distribution. If the statistic is too significant, the assumption of constant error volatility is rejected, which means that heteroskedasticity is present. (Horst Rottmann and Benjamin R. Auer, 2017)
The conduction of the test for the given function of the fixed model is leading to the following results:

LCR: fixed_model - BP = 22.053, df = 4, p-value = 0.0001956

NSFR: fixed_model - BP = 43.307, df = 4, p-value = 8.935e-09

For the regression on the LCR, the test shows a Breusch-Pagan statistic of 22.053, four degrees of freedom and a p-value of 0.0001956. The value of the BP is very strong, while the p-value is significant below the 0.05 threshold. This indicates that heteroskedasticity is present in the regression. Similar is valid for the regression on NSFR. The test shows a Breusch-Pagan statistic of 43.307 with four degrees of freedom and a p-value of 8.935e-09. The BP is even stronger, indicating a stronger presence of heteroskedasticity. The very small p-value confirms the presence. The higher test statistic of NSFR compared to LCR suggests that the issue is even more prominent for the NSFR regression. The strong heteroskedasticity in the sample shows that the variance of the ratios is not constant across the sample of banks and the periods. It seems that the used predictors influence the ratios differently over time. Standard errors are applied to address heteroskedasticity and ensure the regression results' validity, as explained in chapter 5.3.

5.3 Model Adjustments

The results of 5.2.5 and 5.2.3 showed that the two regressions on LCR and NSFR and its predictors are affected by heteroscedasticity and serial correlation, the analysis will be adjusted by using robust standard errors, particularly Driscoll-Kraay standard errors. Standard errors are a method of adjusting standard errors in a panel data analysis. (Daniel Hoechle, 2007, p. 284) By adding them, the model becomes robust to cross-sectional and temporal dependence. A key advantage is that they are reliable regardless of the amount of data, unlike other methods that become unreliable in large datasets. (Daniel Hoechle, 2007, p. 284) Additionally, to the robust errors, yearly dummy variables were added based on the results from the Hausmann test.

5.4 Time series analysis

In a first step of the overall analysis, a simple time series analysis is executed to see how the ratios developed over the given time horizon without including further parameters. The results shall help gain an understanding of the ratios and help plan further analysis steps. For the calculation of the trend as listed in Table 15 - LCR Statistics (2015-2023) in Appendix B, the liquidity coverage ratio increases over the years. Starting with a median of 1.30 in 2015, the ratios increased until 1.5845 in 2019. Between 2019 and 2020, a jump of the median to 1.93 is visible where it reaches its highest point. Afterwards, the median is decreasing again. The median development follows the assumption of increasing liquidity ratios and holding because of the pandemic. This can also clearly be seen in Figure 1 - LCR Trend 2015-2023, marked by the black lines in the boxplots.

The mean of the LCR starts at 1.40 in 2015 and increases continuously over the years until 2021, where it reaches its highest point of 2.04. The median and mean also show that banks improved their liquidity buffers over time, especially during the COVID. The lowest point of standard deviation was similar to the previous results, 2015, which were 0.39. From 2016 onwards, the standard deviation increased with a peak in 2019, as to be seen in Figure 1 - LCR Trend 2015-2023. After COVID, the standard deviation stays high, which indicates that banks have different strategies for their liquidity holdings. Summing up, it can be said that evidence is visible, both directly in the data, as well as in the plotted results, that the liquidity was affected by the financial uncertainty of COVID.

As listed in Table 16 - NSFR Statistics (2015-2023) Appendix B, the net stable funding ratio shows a similar development compared to the liquidity coverage ratio. The overall development shows a steady increase over the years. Starting with a median of 1.153 in 2015, the ratio increases to 1.230 in 2019. From 2019 to 2020, a jump is visible in the median to 1.280. This can also be Figure 1 - LCR Trend 2015-2023 The jump is followed by a further increase to 1.343 in 2021, where the highest value is reached, which goes along with the assumption that COVID leads to increased liquidity holding in response to the financial uncertainty, as 2021 the main phase of

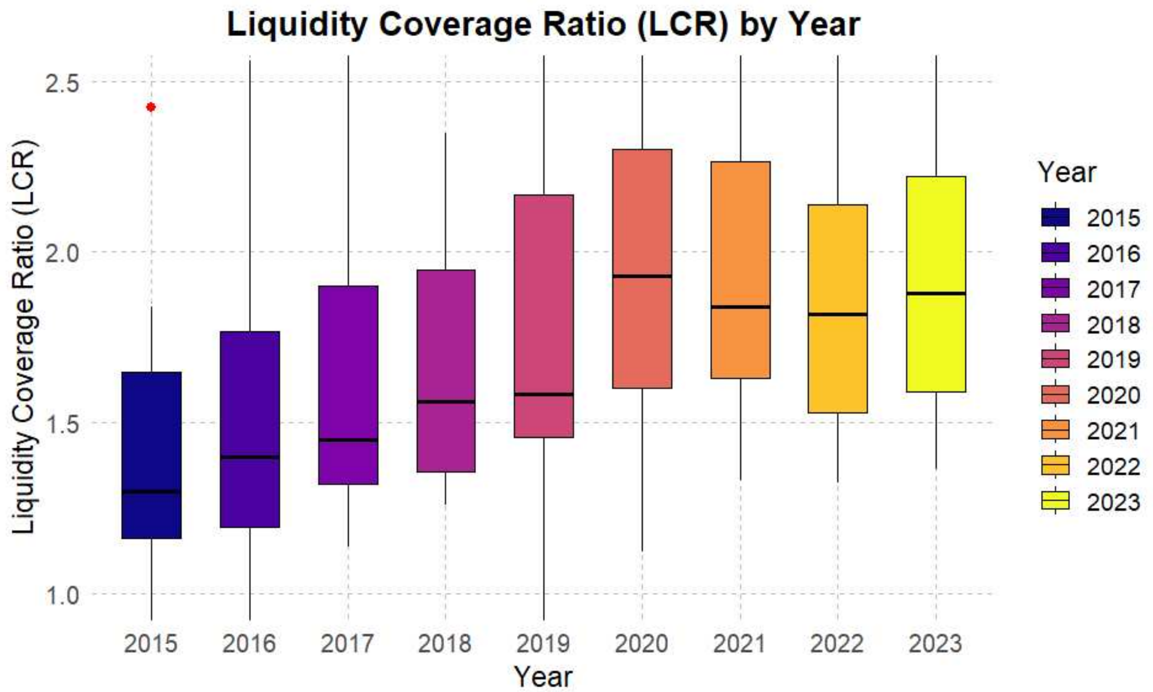

Figure 1 - LCR Trend 2015-2023

COVID was in place. The mean of the NSFR follows a similar development. It starts at 1.138 in 2015 and increases until its peak of 1.365 in 2021. Afterwards, it decreased slightly again, but stayed higher than before COVID. The standard deviation has its lowest point in 2017 at 0.124. Afterwards, it increases until the peak of 0.175 in 2022. The results show that banks, on the one hand, increased their NSFR, but the variation also increased. This means the banks' behaviour is developing in different directions over time. As the standard deviation is higher after 2020, the banks might have different approaches to handle their long-term liquidity after COVID.

The results show that LCR and NSFR increase over time. Both have a peak during

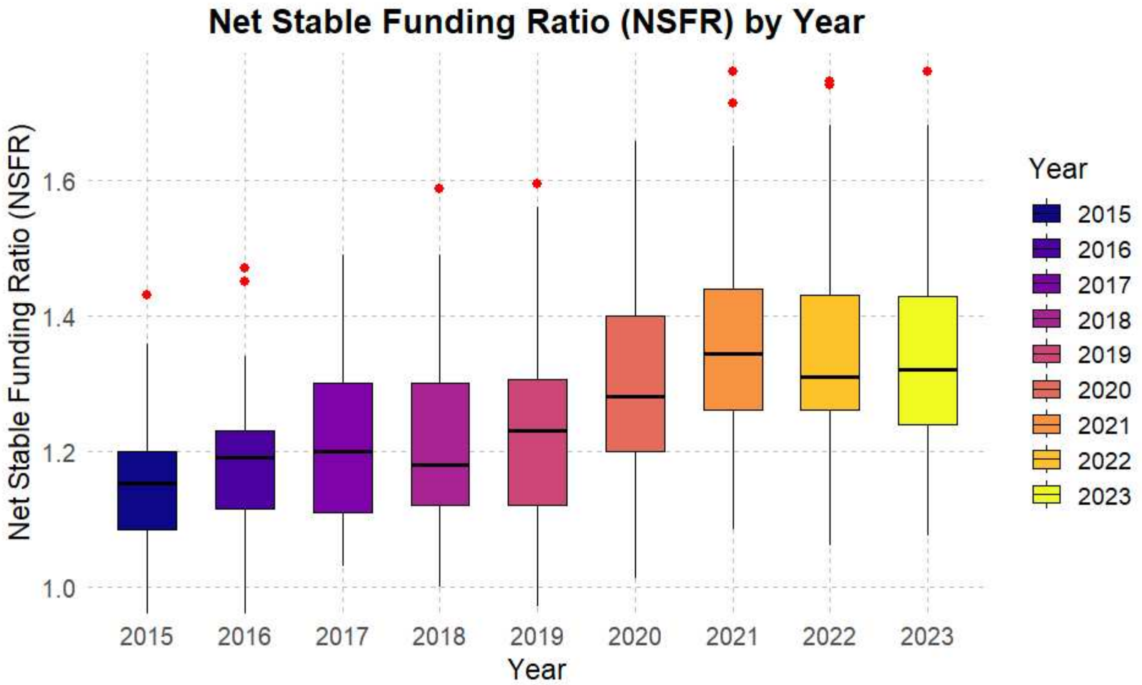

Figure 2 - NSFR Trend (2015-2023)

the COVID pandemic, which suggests the hypothesis that banks strengthened their liquidity positions because of the financial uncertainty. After 2021, both ratios slightly decrease but remain above the level before COVID. As these results only show the development of the ratios from a straightforward approach, without including further parameters, the data will be analysed in a more detailed way in the following chapters.

Besides the development of the two main ratios of this thesis, it is also interesting to investigate how the stability of the banks has developed during the observation period. Therefore, the key statistics of the Z-Score can be used. The average results of the Z_score are listed in Table 1 - Z_score. Additionally, the development over the whole period is plotted in Figure 8 - Z_Score (2015-2023) in Appendix B.

Table 1 - Z_score

Mean	Median	Standard_Deviation	Minimum	Maximum
39.89132	33.8897	431.36137	0.7613967	170.3423

From the figure, it can be seen that from 2015 to 2017, the Z_score increased and therefore the stability of the sample banks. Afterwards, the Z_Score decreases until it reaches its lowest point in 2020, indicating the economic crisis caused by COVID. The data shows that the pandemic affected not only the liquidity but also the overall stability. After 2020, the Z-score increased very sharply. A strong recovery of the economy can explain this after the first uncertainty of COVID in the market was decreasing. Banks improved their financial positions again.
Looking at data points in the table, the average Z_score is 39.89. It has a median of 33.89 and high variation between banks. The wide difference between minimum and maximum is especially interesting. Some banks were very stable, reaching a z_Score of 170.34, while at least one other bank has a Z_Score nearly zero, which indicates a close bankruptcy.

5.5 Structural Break tests

As seen in chapter 5.4, there seems to be a significant increase in the NSFR and LCR between 2019 and 2020, while it stays constant afterwards. To test these observations, the analysis of this thesis is continuing with the test for structural breakpoints. The tests are performed by using the Bai-Perron structural break analysis, which is an algorithm which detects breakpoints in linear regressions and was initially published by Bai and Perron, 1998 and from then on, used in several papers. The approach in this thesis follows the explanation by Thomas A. Doan, 2025. The calculation is done using the regression formulas for LCR and NSFR. The results are listed in Table 2 - Structural Breakpoints for LCR and Table 3 - Structural Breakpoints for NSFR

Table 2 - Structural Breakpoints for LCR

m	Breakpoints Ob	Breakpoints_Dates
1	168	0.414814814814815
2	154, 214	0.380246913580247, 0.528395061728395
3	94, 154, 214	0.232098765432099, 0.380246913580247, 0.528395061728395
4	89, 190, 261, 321	0.219753086419753, 0.469135802469136, 0.644444444444444, 0.792592592592593
5	61, 130, 190, 261, 321	0.150617283950617, 0.320987654320988, 0.469135802469136, 0.644444444444444, 0.792592592592593

Table 3 - Structural Breakpoints for NSFR

m	Breakpoints Observation Points	Breakpoints_Dates
1	99	0.244444444444444
2	98, 314	0.241975308641975, 0.775308641975309
3	99, 223, 314	0.244444444444444, 0.550617283950617, 0.775308641975309
4	111, 172, 232, 314	0.274074074074074, 0.424691358024691, 0.57283950617284, 0.775308641975309
5	72, 132, 192, 254, 314	0.177777777777778, 0.325925925925926, 0.474074074074074, 0.62716049382716, 0.775308641975309

The results for LCR (Table 2 - Structural Breakpoints for LCR) show exiting breakpoints especially at the observation points 154, 190, 214, 261, and 321. These results are according to the breakpoint dates. For NSFR (Table 3 - Structural Breakpoints for NSFR), breakpoints occur at 99, 223, 232, 254, and 314 and the corresponding dates. These breakpoints can be converted into actual years. As the sample in the thesis has data points from 2015 to 2023, it means for the LCR, there are breakpoints around 2016, 2019, 2020 and 2021, for the NSFR breakpoints can be found in 2016, 2018, 2020 and 2021. The results prove that 2020 is a precise breakpoint, which correlates with the thesis's assumption that COVID impacts the liquidity ratios. Also, clearer breakpoints were expected, and the results show a pattern of breakpoints in 2019, 2020, and 2021, which goes along with the assumption of the thesis. The breakpoints in 2020 and 2021 in both LCR and NSFR align with the pandemic's peak, accompanying a period of financial uncertainty. Also, the results already show evidence for the effect of COVID on the liquidity ratios, further analysis is required to prove the assumption of the thesis. The additional analysis will be conducted in the following chapter. Based on the results from the structural breakpoint test above, the sample will therefore be divided into three phases: A pre-COVID phase (2015–2019), followed by a during-COVID phase (2020–2021), and a post-COVID phase (2022–2023).

5.6 Analysis of the Variance

As described in the previous chapter, the structural breakpoints only partially prove COVID's effect on the liquidity ratios. For further analysis, an ANOVA (Analysis of Variance) is conducted. According to Will Kenton, 2024 an ANOVA is a statistical test used to compare the means of more than two groups. In the case of this thesis, the sample will be split up into three groups(phases): A pre-COVID phase (2015–2019), the during-COVID phase (2020–2021), and the post-COVID phase (2022–2023). The ANOVA helps to analyze if the difference between these three phases are caused by coincidence or are based on explainable reasons. For the conduction of the analysis, a one-way ANOVA is used as one independent variable is given (LCR and NSFR). ANOVA is widely used in research, not only in the field of finance but also in other disciplines such as medicine. (Will Kenton, 2024) It is therefore a useful approach for analysing the two liquidity ratios. The following two chapters split the results for the liquidity coverage ratio and net stable funding ratio. A Shapiro Wilk test is conducted to test if the sample follows a normal distribution. The test compares a normal distribution's expected variance with the sample's actual variance. If the p-value is smaller than 0.05, the data are not normally distributed, if the p-value is above 0.05, the sample is usually distributed. (Robert Grünwald, no date). Furthermore, a Levene`s test will test the sample for homogeneity. The test checks whether the different phases have the same variance. The variances are not significantly different if the p-value is greater than 0.05. If the p-value is less than 0.05, the variances are significantly different. (DATAtab Team, 2025). Finally, it is essential to introduce the Tukey Honest Significant Difference (HSD). The test analyses, which phase, after the conduction of an ANOVA, has shown significant differences between the means. It helps to identify which specific group means are significantly different from each other. It compares all possible pairs of phases means to see where the differences are. (Biostats, no date)

5.6.1 LCR

The key results of the analysis of the variance are listed in Table 4 - ANOVA Results for LCR.

Table 4 - ANOVA Results for LCR

Variable	DF	Sum_Squares	Mean_Squares	F_Value	P_Value	Dependent_Var
Factor (Phases)	2	8.522488	4.2612438	14.73761	0.0000006649365	LCR
Residuals	403	116.523744	0.2891408			LCR

The results show a very significant difference between the phases. The factor of the phases has a value of 8.52. Dividing the value by the degrees of freedom, the result for the mean is 4.26, which is the average variation of the LCR because of the phases. The sum of the squares of the residuals is 116.52. This value represents the overall variation within each phase that the time phase itself cannot explain. The results show clearly that the mean square of 0.289 is much smaller than the mean square for periods 4.26. The F-value of 14.74 is calculated by dividing the mean square for the phases (4.26) by the mean square of the residuals (0.289). The value of 14.74 is very high. This proves that the variation between the phases is much more important than the variation within them. The p-value is very small, confirming that these differences are statistically significant and not caused by random impacts. Therefore, the thesis's assumption has been proven, that the liquidity ratios varied between the COVID phases.

The two additional tests were conducted as described in 5.6 to confirm the analysis results. The results of the tests are listed in

Table 17 - ANOVA Tests in Appendix B. The Shapiro-Wilk Test has a W-value of 0.89991 and a p-Value of 1.1114e-15. The test indicates that the data is not perfectly normally distributed. Also, the p-value is very small, due to the robustness of the ANOVA, the results still remain reliable. Confirmed by the fact that the W-value is close to 1. The Levene´s test results are in an F-Value of 0.28840 and a p-value of

0.7496. These results indicate that the variance of the LCR is consistent across the three phases. Based on the two tests, it can be said that the results are valid. As the results of the ANOVA do not explain which phases the just proven differences appear in the following step a Tukey HSD is performed. The results of the Tukey HSD are listed in Table 5 - Tukey HSD LCR. In the first line, the comparison between the COVID phase and the pre-COVID phase is listed. It shows a difference of 0.3289 and a confidence interval between the lower bound of 0.173 and the upper bound of 0.4836. Both values are positive, indicating that the LCR was significantly higher during COVID than pre-COVID.

Table 5 - Tukey HSD LCR

Comparison	Difference	Lower_CI	Upper_CI	P_Value	Dependent_Var
2-1	0.32892597	0.1732765	0.48457541	0.000002945621	LCR
3-1	0.26777191	0.1185688	0.41697502	0.000088763290	LCR
3-2	-0.06115405	-0.2197552	0.09744706	0.636157404695	LCR

The p-Value is given by a minimal number of 0.0000029, which confirms the result. Banks seem to have increased their short-term liquidity holdings because of the pandemic.

In the second line, the comparison between post-COVID and pre-COVID is shown. Here, the results show a difference of 0.2678, with a confidence interval between 0.1186 and 0.4170. The p-Value is again very small with 0.0000888. This indicates that the LCR remained significantly higher post-COVID than the pre-COVID phase. It seems that the banks kept higher liquidity ratios after COVID.

The last line shows the comparison results between the post-COVID phase and the during-COVID phase. They have a difference of -0.0612, with a confidence interval between -0.2198 and 0.0974. The p-Value is quite significant at 0.6362. Therefore, the results are statistically not significant. The results show that the LCR did not change significantly between the during-COVID and post-COVID phase. This suggests that banks maintained similar liquidity levels even after the pandemic's peak, and it goes along with the results of comparing the second line.

To summarise the results, Figure 3 - LCR across phases, can be used. The boxplots show the results explained by the ANOVA and Tukey HSD. It can clearly be seen in the first boxplot that before COVID, the liquidity ratios were lower. During COVID,

there is a clear increase in the LCR. This indicates that banks reacted to the pandemic by increasing their liquidity. Also visible is a higher median and at least slightly broader spread in the during COVID phase compared to the pre-COVID phase.
In the post-COVID phase, the LCR remains at a very similar level compared to during COVID, as shown by the comparable distributions.

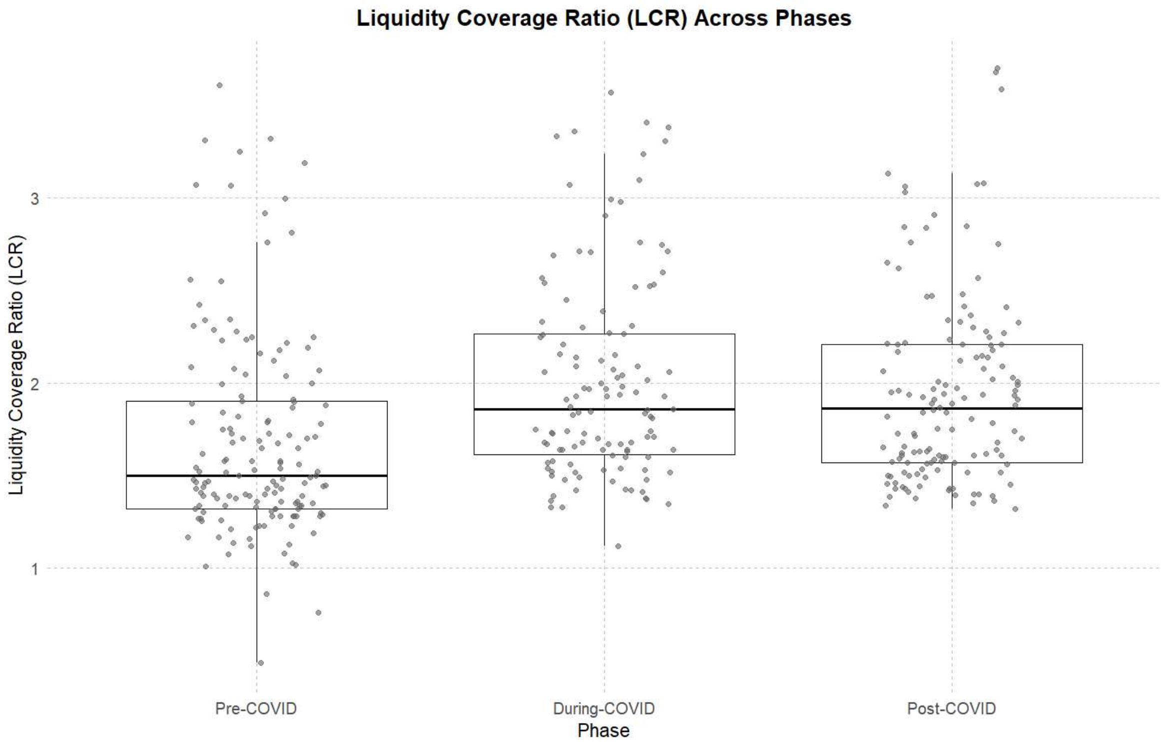

Figure 3 - LCR across phases

5.6.2 NSFR

The same approach was used for the analysis of the NSFR. The key results of the variance analysis are listed in Table 6 - ANOVA Results for NSFR.

Table 6 - ANOVA Results for NSFR

Variable	DF	Sum_Squares	Mean_Square	F_Value	P_Value	Dependent_Var
Factor (Phases)	2	1.914031	0.9570157	41.09973	0.0000000000000000005701946	NSFR
Residuals	403	9.383937	0.0232852			NSFR

The sum of the squares for the phases factor of 1.91 is lower than for LCR. The mean is 0.957, which also describes the average variation of the NSFR caused by the phases. The mean of the square for residuals is 0.023, which is much smaller than the mean square for the phases (0.96). This result shows that the variation between the phases is far more critical than the variation within them. The F-value of 41.10 is very high. This proves that the NSFR changed significantly between the three phases. The very low P-value proves the existence of very significant differences in the NSFR between the three phases, which goes along with the assumption that the long-term liquidity positions have changed over the COVID phases.
To confirm the results, a Shapiro-Wilk and Levene's tests were conducted. The results are stored in

Table 17 - ANOVA Tests in Appendix B. The Shapiro-Wilk test results in a W-value of 0.96962 and a p-value of 1.799e-07. This indicates that the residuals are not perfectly normally distributed. Similar to LCR, the W-value is near 1, and the robustness of the ANOVA handles slight deviations from normality. Therefore, the results remain valid. The Levene's test results in an F-value of 1.5298 and a p-value of 0.2178. This means that the variance of the NSFR is consistent across the three phases.
According to the procedure for the LCR, a Tukey HSD is performed to specify between which phases the differences occur. The results are listed in Table 7 - Tukey HSD NSFR.

Table 7 - Tukey HSD NSFR

Comparison	Difference	Lower_CI	Upper_CI	P_Value	Dependent_Var
2-1	0.1295917	0.08542114	0.17376225	0.00000000003870482	NSFR
3-1	0.1510574	0.10871619	0.19339860	0.00000000000000000	NSFR
3-2	0.0214657	-0.02354250	0.06647389	0.50109171545465458	NSFR

The first comparison looks at the values from the during and pre-COVID phases. The difference is given by 0.1296 with a confidence interval between 0.0854 and 0.1738. This confirms the assumption of the thesis that NSFR was significantly higher during COVID compared to pre-COVID. The p-value is extremely small, proving the result is highly significant. Banks seemed to have increased their long-term liquidity in response to the pandemic. The second comparison in line two compares the post-COVID phase to the pre-COVID phase. The difference here is 0.1511, with a confidence interval between 0.1087 and 0.1934. Also, the results confirm that the NSFR remained significantly higher post-COVID than pre-COVID. The p-value is effectively zero. This prove is also highly significant and indicates that banks did not return to liquidity levels before the pandemic; instead, they continued to hold higher NSFR values. The third comparison looks at the post-COVID phase compared to the during-COVID phase. Here, the difference is only 0.0215, with a confidence interval between -0.0235 and 0.0665. Since the confidence interval includes a zero and the p-value of 0.5011 is relatively high, the result is statistically insignificant. This means the NSFR did not change significantly between the during-COVID and post-COVID phases. Banks seem to have kept their higher liquidity even after the pandemic's peak, which aligns with the previous results. To summarize the finding,

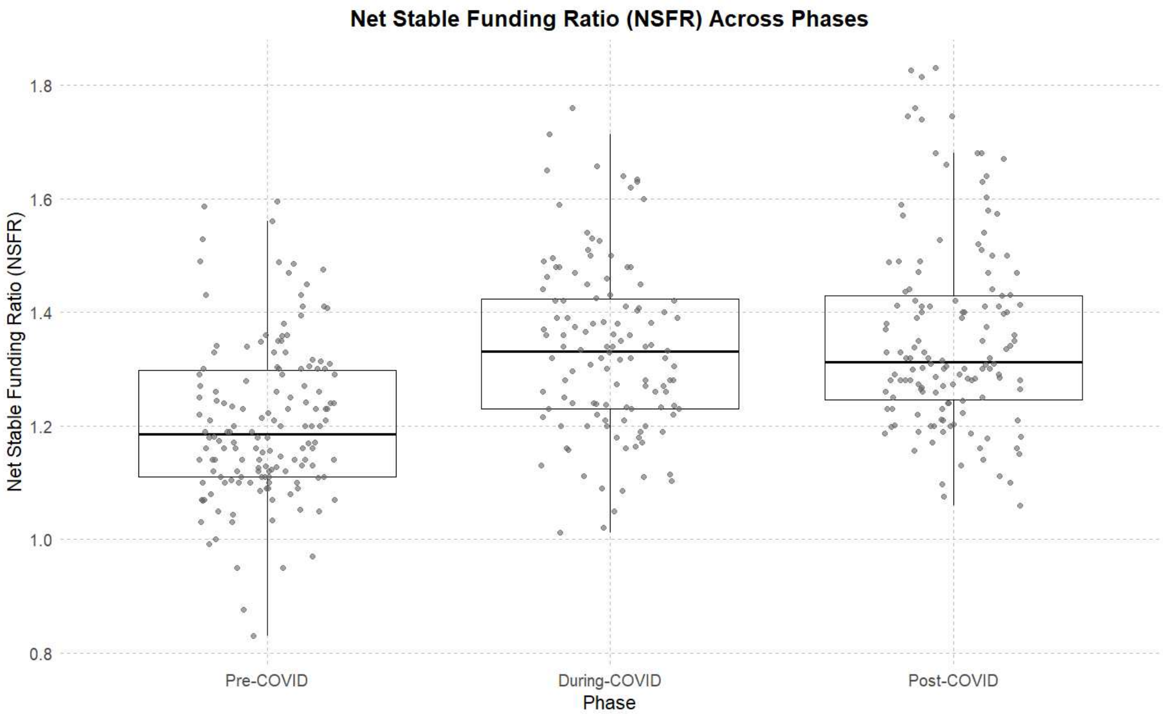

Figure 4 - NSFR across phases shows a plotted overview of the ANOVA and Tukey HSD results. The boxplots clearly show that before COVID, NSFR was lower, while during COVID, there was an apparent increase. Therefore, the thesis's assumption is also graphically proven that banks adjusted their long-term liquidity ratios in response to the crisis.

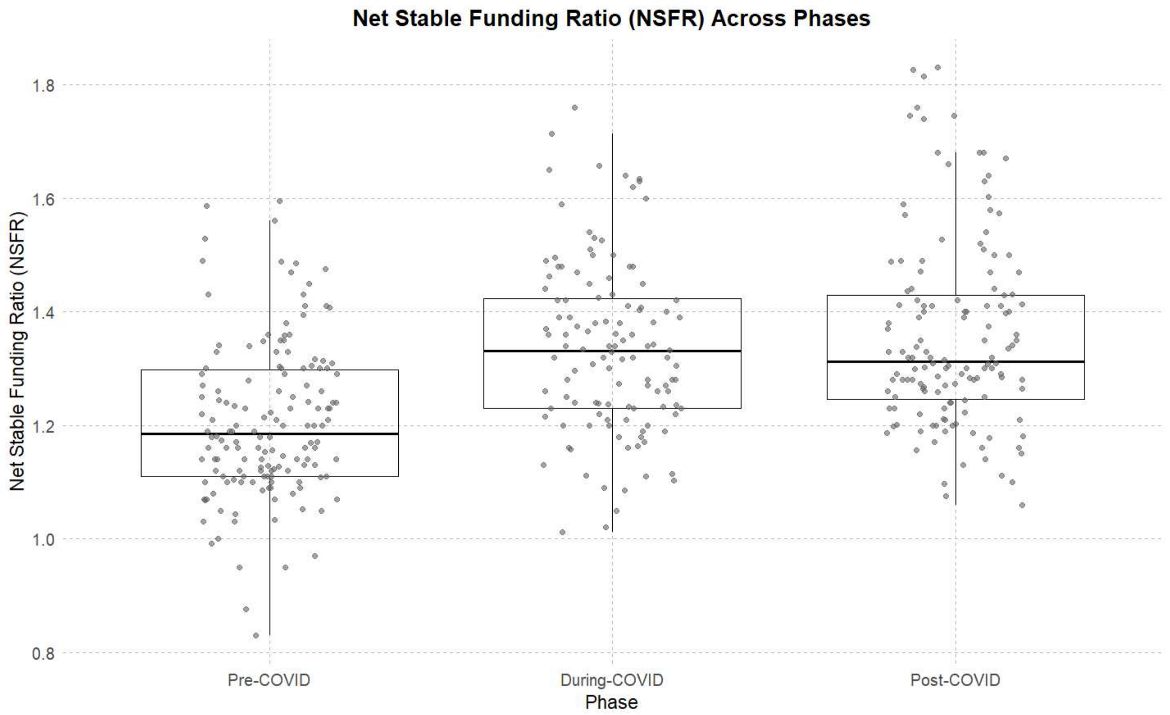

Figure 4 - NSFR across phases

Looking at the median, one can see that it increased during the COVID phase. The spread of values is wider, which confirms the variation observed before. In the post-COVID phase, NSFR remains at a similar level as during COVID, as shown by the overlapping distributions in the boxplot, which goes along with the results for the LCR.

Combining the results of NSFR and LCR, it can be said that both increased significantly during COVID and remained high for the post-COVID phase. However, the changes in NSFR were even more substantial, as shown by the higher F-value (41.10 vs. 14.74 for LCR). The Tukey HSD test confirms that both ratios increased significantly from the pre- to during-COVID phase and stayed relatively constant in the post-COVID phase. The comparison of the post- to the during-COVID phase was, in both cases, not significant. The boxplots additionally support these results. Both ratios show a clear increase during COVID and no return to pre-pandemic levels afterwards.

5.7 Regression Testing for Liquidity Drivers

As proved in the previous chapters, the liquidity coverage ratio and net stable funding ratio changed because of COVID. Nevertheless, there might be further reasons for the increase of the ratios. To limit external factors that might influence the ratios, the parameters used for the regression analysis and variations between pre-, during, and post-COVID phases are tested. As in the previous chapter, variance analysis is performed. The results are listed in Table 8 - ANOVA for Predictors.

Table 8 - ANOVA for Predictors

Variable	DF_Factor	DF_Residuals	F_Value	P_Value
Z-Score	2	403	1.366059	0.256289153
GDP Growth	2	403	5.916871	0.002933195
Bank Size	2	403	6.759322	0.001296063
Cost-Income Ratio	2	402	5.324623	0.005219689

The results show that no significant change over time appears for the Z-Score, as the p-value of 0.256 is too high. This means that the bank stability remained unchanged throughout the three COVID phases. The same is valid for the GDP growth with a p-value of 0.613. This shows that the variations in GDP growth between the observed banks were not statistically significant. In contrast to these results, the bank size shows a significant change across the phases, with a very low p-value of 0.0013. This indicates that the size of banks also changed over the COVID period, which might have impacted the changes in liquidity ratios. The cost-income ratio also shows a statistically significant difference, with a p-value of 0.00522. The results indicate that the efficiency of the banks varied across the three phases, which might as well have an impact on the liquidity ratios.

Further analyses are performed to exclude the option that the changes in the liquidity ratios are simply a result of banks growing in size or performance, or if the pandemic itself had an independent effect. To test this, a regression model is used where the liquidity ratios are used as dependent variables while bank size and cost-income ratio are used as predictors. The regression uses factor(Episode), where the pre-COVID phase is the baseline, and the outputs for factor(Episode)2 and factor(Episode)3 show how the liquidity ratios compared to the pre-COVID phase were changing. If the two predictors (Cost Income Ratio and bank size) are the main drivers of the liquidity changes, and therefore not COVID, their effect would be statistically significant, and the impact of COVID would be weaker. The results of the regressions are listed in

Table 9 - Regression for LCR and Table 10 - Regression for NSFR.

Table 9 - Regression for LCR

Variable	Estimate	Std..Error	t.value	p.value	Significance
factor(Episode)2	0.3699267	0.08193493	4.5148840	0.000008836609	***
factor(Episode)3	0.3044089	0.07925268	3.8409923	0.000147006506	***
ln_Size_EUR	-0.0138043	0.12680811	-0.1088598	0.913380087136	
Cost_income_ratio	-0.1488372	0.32006920	-0.4650156	0.642227887012	

Table 10 - Regression for NSFR

Variable	Estimate	Std..Error	t.value	p.value	Significance
factor(Episode)2	0.15198531	0.03175379	4.786368	0.00000257003019379814	***
factor(Episode)3	0.16820586	0.02119328	7.936754	0.0000000000003296238	***
ln_Size_EUR	0.05287158	0.02682289	1.971136	0.04954606110955867698*	
Cost_income_ratio	-0.15304306	0.07311565	-2.093164	0.03709994944760276053*	

For LCR, the during and post-COVID phases increase significantly compared to the baseline, which goes along with the overall idea of this regression. Interesting to see is that the impact of bank size on LCR is statistically insignificant, which means that the increase in the liquidity ratio cannot be explained by bank growth. The same is true for the cost-income ratio, which is also statistically insignificant and, therefore, cannot explain the increase in the liquidity coverage ratio. These results prove that COVID itself plays a key role in influencing short-term liquidity. These results support the analysis in Chapter 5.6 and demonstrate that at least the parameters used in this thesis have no influence on the development of short-term liquidity.

For NSFR, the results are similar. The during and the post-COVID phases have significantly increased compared to the pre-COVID phase. The outputs for Factor (Episode)2 and Factor (Episode)3 are highly significant. Unlike the results for LCR, bank size has a statistically significant effect on NSFR. It shows that larger banks have different liquidity developments compared to smaller banks. Also, the cost-income ratio has a considerable impact on NSFR. This leads to the conclusion that the efficiency of banks plays a role in the changes of the net stable funding ratio.

Nevertheless, the findings show that COVID had an independent impact on NSFR. Also, the bank size and efficiency impacted the liquidity development; they do not fully explain the increase of the NSFR during and after the pandemic. The results also support the analysis in Chapter 5.6, even though not as strong as for LCR.

The results strengthen the conclusion that COVID had an independent impact on the liquidity positions of European banks. Nevertheless, it must be considered that this thesis only proves the influence of the four parameters, which, of course, cannot fully explain all effects on the key ratios as described in chapter 4.5. Future analyses can build on this topic and verify the findings using additional parameters and approaches.

5.8 Regression Analysis

Besides the impact of COVID on the liquidity ratios, which was analyzed in the previous chapter, the thesis also investigates the effects of different factors influencing the ratios. The analysis is conducted by a panel regression with fixed effects. The decision to use this approach is based on the results of the statistical test in chapter 5.2. The predictors used and the reason why they were chosen are explained in Chapter 4.5. As described in this chapter, the following predictors are used: Z_Score, to determine the stability of the bank; bank size, to measure if larger banks have a different behavior while maintaining their liquidity ratios; the economic conditions, measured by the GDP Growth of the country the bank is stated; and the profitability, measured by the Cost income ratio. Using these predictors will deliver results to the question of the relationships between these factors and the liquidity ratios between the pre- and post-COVID phases. In contrast to the previous chapter, a different approach is used in the following regression models. Instead of dividing the sample into three phases, the sample is now only divided into two phases: a pre-COVID phase (2015-2019) and a post-COVID phase (2022-2023). Excluding the actual COVID phase shall deliver more accurate data about the adjustments of the predictors. The analysis is not interested in the impact during the pandemic but in the structural changes and long-term adjustments that occur in response to the pandemic. Additionally, excluding the COVID phase shall reduce potential data inconsistencies caused, for example, by government interventions during COVID. The analysis is divided into a chapter for the LCR and a chapter for the NSFR, while both chapters follow the same approach. First, a simple regression is conducted as a baseline. It shall provide an initial view of the relationships between the predictors and the dependent parameters without controlling for external influences. In the next step, the regression is extended by time-fixed effects to improve the meaningfulness of the study by accounting for the factors that change over time and affect all observations. Finally, a fully saturated model is calculated, including the time-fixed and entity-fixed effects that account for differences between the observations that stay the same over time. This stepwise approach shall ensure that the conclusions are based on actual changes rather than external effects.

5.8.1 LCR

In Appendix B, Table 18 - Naive Regression Model - LCR and Table 20 - Time Fixed Model - LCR, key differences are visible when comparing the pre-COVID phase to the post-COVID phase. Looking at the naïve regression, the results show that the intercept is increasing from the pre-COVID phase to the post-COVID phase, which goes along with the results of the previous chapters and additionally proves the increase of the ratio caused by COVID. The Cost income ratio was not significant in the pre-COVID phase but became negative and significant after COVID. This indicates that banks with higher costs relative to their income seem to hold less liquidity in the short term. The GDP growth was not significant before COVID but was significant after COVID. Also, the beta turned positive. The bank size had a negative effect on the liquidity coverage ratio in both phases, but it increased in the post-COVID phase. The result shows that larger banks held less short-term liquidity over time. Finally, the Z_Score was insignificant in both phases, meaning that the bank's stability did not affect the liquidity holdings. The intercept remains higher in the post-COVID phase in the time-fixed effects model. The cost-income ratio is no longer significant. The result indicates that other effects may have influenced the observed effect in the naïve model. The GDP growth remains positive and considerable post-COVID. The bank size stays negative and even stronger in the post-COVID phase. Z_Score remains non-significant.

Using the results from both models, the results of the fully saturated model become more valid. The results are listed in Table 11 - Fully Saturated Regression Model - LCR.

Table 11 - Fully Saturated Regression Model -LCR

Period	Predictor	Estimate	Std. Error	t value	Pr(>|t|)Signif
Pre-COVID	Cost_income_ratio	0.094	0.469	0.201	0.841158
Post-COVID	Cost_income_ratio	-0.048	0.518	-0.092	0.926871

Period	Predictor	Estimate	Std. Error	t value	Pr(>|t|)Signif
Pre-COVID	GDP_growth	0.011	1.083	0.010	0.992009
Post-COVID	GDP_growth	-0.732	0.790	-0.926	0.358327
Pre-COVID	factor(Year)2016	0.117	0.103	1.132	0.260397
Pre-COVID	factor(Year)2017	0.243	0.100	2.427	0.017092*
Pre-COVID	factor(Year)2018	0.378	0.102	3.727	0.000326***
Pre-COVID	factor(Year)2019	0.448	0.106	4.246	0.000050***
Post-COVID	factor(Year)2023	-0.027	0.076	-0.354	0.724466
Pre-COVID	ln_Size_EUR	-0.309	0.308	-1.001	0.319474
Post-COVID	ln_Size_EUR	2.197	1.010	2.175	0.033590*
Pre-COVID	z_Score	-0.003	0.009	-0.323	0.747555
Post-COVID	z_Score	0.022	0.012	1.867	0.066786

The fully saturated model includes both, time-fixed effects and bank-fixed effects. This means it provides control over the changes in time and differences between the banks. The context of the analysis shall help to deliver more precise results and explain how the impact of the predictors changed before and after COVID. The predictors show that the cost-income ratio, which was significant in the naïve model after COVID, is no longer important in both phases. Interestingly, before COVID, it had a positive beta of 0.094 with a p-value of 0.841. In contrast, after COVID, the beta became negative with a value of -0.048 and a higher p-value of 0.927. Compared to the previous models, the results show that the effects came from factors instead of having a direct impact on the short-term liquidity. The change from a different positive to a negative beta is not to be analysed further because of the non-significance.

The impact of the GDP growth, which was positive and significant in the time-fixed model after COVID, is now negative and not significant anymore. Before COVID, it had a beta of 0.011, which was already not significant. After COVID, the beta turned negative to a value of -0.732 with a p-value of 0.358. The results show that GDP growth does not seem to have an apparent effect on short-term liquidity. Unlike the two previous predictors, bank size impacts the LCR and is an interesting shift. Before COVID, the beta was negative with a value of -0.309. However, the results were not significant. Nevertheless, the results indicate that larger banks seemed to hold less liquidity in the short term. After COVID, these results have now changed. The beta became positive and significant, with a value of 2.197 and a p-value of 0.034.

The results indicate that larger banks actually increased their liquidity coverage ratio after the pandemic in contrast to the two simpler models. There are different reasons why this effect applies. One idea might be that because of the uncertainty, large banks adjusted their responses to the regulatory requirements as the internal risk assessment was adjusted and became stronger. The banks seem to have become more cautious and decided to maintain higher liquidity buffers to prepare for potential future uncertainties in the financial markets.

Finally, looking at the z_Score. It was not significant in the naïve or time-fixed models. In the fully saturated model, it remains non-significant before COVID with a beta of -0.003 and a p-value of 0.748. After COVID, it becomes marginally significant with a beta of 0.022 and a p-value of 0.067.

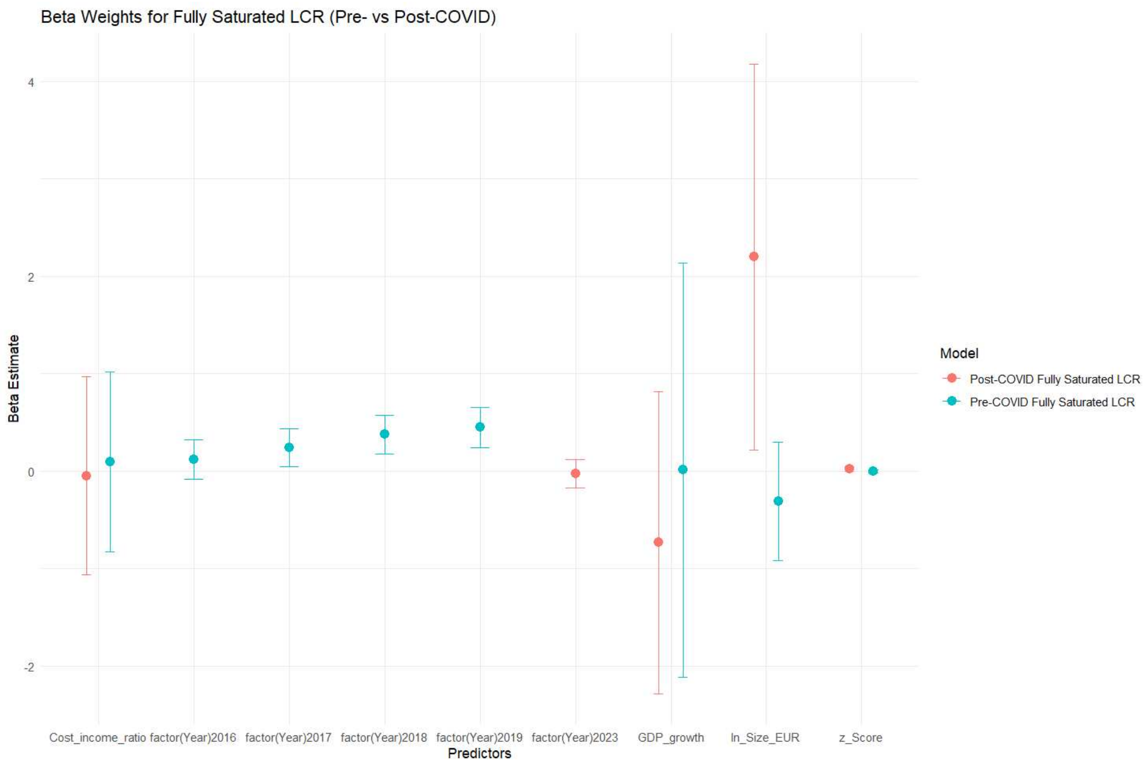

Figure 5 - Beta weights Fully saturated LCR model

Interesting to see that also, for the z-value, the beta changed between a negative and positive value because of COVID. It seems that the bank stability might have played a more significant role in the liquidity coverage ratio after COVID. Nevertheless, the effect is minimal. The above described results can also be seen in Figure 5 - Beta weights Fully saturated LCR model. The figure visualises the beta estimators for the fully saturated LCR model. It compares the pre-COVID and post-COVID phases (Red for post-COVID vs light green for pre-COVID). The figure shows how the impact of different predictors changed after the pandemic. The bank size is the most interesting change, which was already seen in the data before. It is also graphically visible that negative beta before COVID became significantly positive after COVID. Also, the change of the GDP growth from a weak effect pre-COVID to a more substantial, but still not very certain influence in the post-COVID phase is visible. Overall, the figure supports the findings from the regression models.

5.8.2 NSFR

The analysis of the NSFR follows the same approach as one of the LCR. The results for the naïve and time-fixed models are listed in Table 19 - Naive Regression Model -NSFR and Table 21 - Time Fixed model - NSFR. The increased intercept in the naïve model proves that the NSFR increased after COVID. That means that, in the long term, banks hold more liquidity after COVID, which goes along with the results shown in the previous chapters. The significance of the cost_income ratio does not change before and after COVID, which means it did not influence the NSFR. The GDP growth had no effect before COVID but became positive after the pandemic. The effect of the bank size, in general, is significant, and it goes along with the results of the LCR. Before COVID, it was negative but not significant. After COVID, the value of the beta decreased even more and became more negative. The p-value became smaller, and therefore, the results were significant. The results show that larger banks reduced their net stable funding because of COVID. The Z_score was not significant before COVID but developed into a negative predictor after COVID, which also became significant.

The trends can be confirmed by comparing the time-fixed model to the results. The intercept remains higher after COVID. The cost-income ratio still does not influence the NSFR. GDP growth has a significant impact on the NSFR after COVID. The negative effect of the size of the banks is even stronger in the fixed-time effects model. The Z_Score remains negative and significant. The results from the two simple models can be compared to the regression results of the fully saturated model, which are listed in Table 12 - Fully Saturated Regression Model -NSFR.

Table 12 - Fully Saturated Regression Model -NSFR

Period	Predictor	Estimate	Std. Error	t value	Pr(>|t|)Signif
Pre-COVID	Cost_income_ratio	-0.017	0.086	-0.200	0.842160

Period	Predictor	Estimate	Std. Error	t value	Pr(>|t|)Signif
Post-COVID	Cost_income_ratio	0.082	0.140	0.589	0.558201
Pre-COVID	GDP_growth	-0.360	0.199	-1.810	0.073329
Post-COVID	GDP_growth	-0.458	0.214	-2.146	0.035928*
Pre-COVID	factor(Year)2016	0.028	0.019	1.491	0.139171
Pre-COVID	factor(Year)2017	0.065	0.018	3.527	0.000644***
Pre-COVID	factor(Year)2018	0.087	0.019	4.667	0.000010***
Pre-COVID	factor(Year)2019	0.105	0.019	5.410	0.000000***
Post-COVID	factor(Year)2023	-0.012	0.020	-0.570	0.570986
Pre-COVID	ln_Size_EUR	-0.062	0.057	-1.101	0.273688
Post-COVID	ln_Size_EUR	-0.363	0.273	-1.328	0.189174
Pre-COVID	z_Score	0.004	0.002	2.339	0.021382*
Post-COVID	z_Score	0.004	0.003	1.380	0.172645

Similar to the simple models, the cost-income ratio remains insignificant in the pre- or post-COVID phases. The results show that the banks' profitability did not directly influence the banks' net stable funding ratio. The p-value changed from 0.842 to 0.558, and both values were too high to conclude any significance. As the beta value is around zero in both phases, no meaningful results can be mentioned here. The GDP growth rate was already significant in the time-fixed model in the phase after COVID. The fully saturated model can confirm this result. Before the pandemic, the beta had a negative value of -0.360 and a too-high p-value of 0.073. The GDP growth rate, therefore, does not influence the net stable funding at that time. After COVID, the effect increased. The beta became even more negative, with a value of -0.458 and a p-value of 0.036; therefore, it was statistically significant. The results indicate that banks reduce their long-term liquidity with a more stable economy.

Looking at the effect of the bank size on the net stable funding ratio, it has another effect than the one for the LCR.

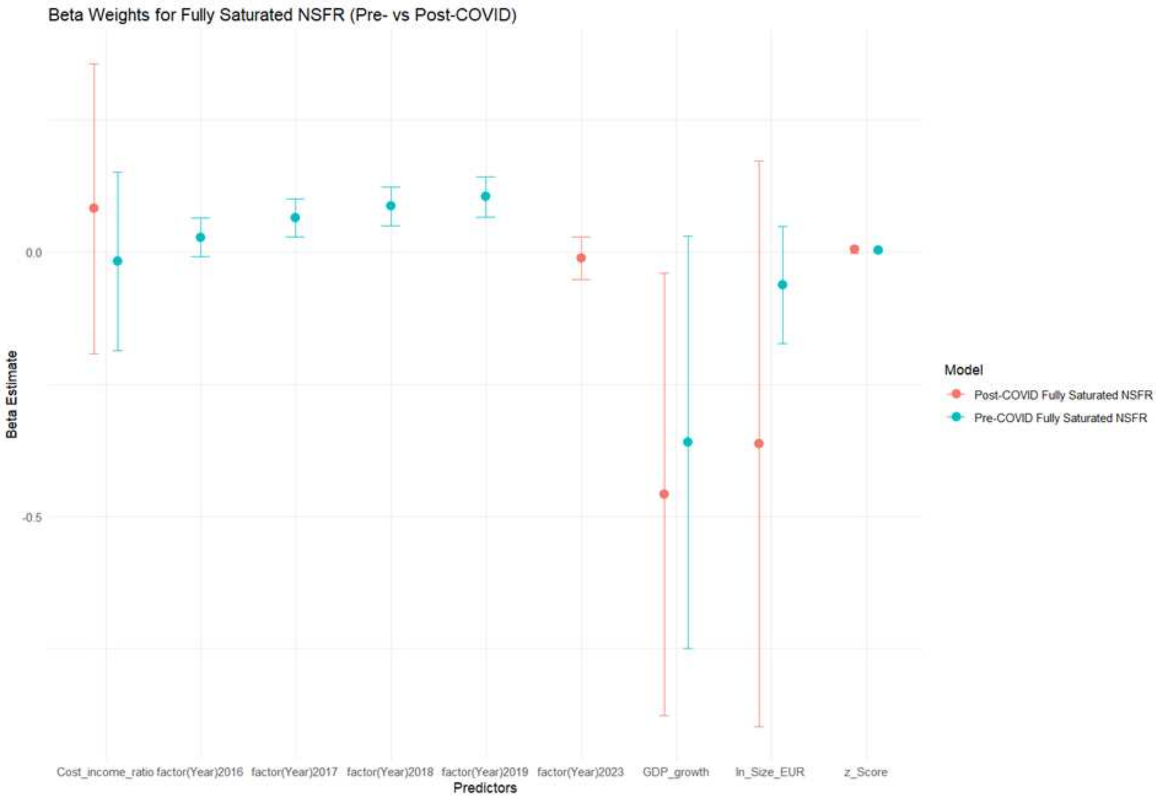

Figure 6 - Beta weights fully saturated NSFR model

The impact of bank size remains negative. In the phase before COVID, larger banks had a lower NSFR, with a non-significant p-value. The negative effect of the bank size became even stronger after COVID, with a beta of -0.363. The results nevertheless stay non-significant with a p-value of 0.189. Larger banks seem to reduce their long-term liquidity even after the pandemic. The Z_score also changed after COVID. Before the pandemic, banks with higher Z_scores had a more stable net funding ratio. Also, the beta value was relatively low at 0.0004. The p-value of 0.021 indicates statistical significance. After COVID, the beta remained at a very similar level but with an increased p-value of 0.173. Therefore, the results are not significant anymore. The results can also be seen in Figure 6 - Beta weights fully saturated NSFR model. The figure shows the beta estimates for the fully saturated NSFR model. As in the liquidity coverage ratio analysis, the pre-COVID predictors are light blue, and the post-COVID predictors are marked red. The key finding from the data analysis is also visible in the figure. Unlike the LCR, which turned positive after COVID, the bank size remains negative in both phases. The negative effect of the

GDP growth before and after COVID is also visible. The Z_score stays on the same level.

6 Conclusion

The thesis follows two main research questions, which were conducted differently. Also, the two main variables, the liquidity coverage ratio and the net stable funding ratios, were split up during the analysis. After delivering key insights into the background of the liquidity management in the banking sector in the Basel Accords, a literature review was conducted to find similar research. Currently, the research on liquidity development during COVID is minimal; therefore, the thesis delivers valuable insights into this area. After explaining how the data was collected and cleansed, it was explained how statistical tests and adjustments were performed to guarantee meaningful results. This section was followed first, by a time series analysis and structural break test, which gave first hints on the results of the two primary analyses.

The first and main research goal investigates how the liquidity positions of European banks, measured by the Basel III liquidity ratios, have changed during the COVID pandemic. An analysis of the variance was conducted for the two variables, where the sample was split into three phases. A pre-COVID phase, a during-COVID phase and a post-COVID phase. The analysis confirms that the liquidity coverage and net stable funding ratios changed significantly due to COVID. Before COVID, both ratios were on an upward trend; the liquidity positions were improving constantly but gradually. The thesis's main result is the very sharp increase of both ratios in the phase during COVID. Banks seem to have responded to the financial uncertainty COVID brought to the market by strengthening their liquidity ratios, as well as in the short and long term. Therefore, their liquidity buffers. After the pandemic, both ratios remain above the pre-COVID levels. The banks did not return to their previous liquidity levels. They keep a higher liquidity in their books to handle future uncertainties.

Also, there are similarities between the development of the LCR and the NSFR, there are differences. While both ratios increased sharply because of COVID and remained stable after the pandemic, the changes of the NSFR were even stronger. The calculated F-value was way higher for the NSFR than for the LCR. It seems that the variations of the long-term liquidity were stronger compared to the short-term liquidity. Overall, the results confirm that COVID significantly impacted the liquidity in the European banking system.

The second part of the thesis focused on how different factors such as the stability of the bank, bank size, economic conditions, and profitability influence LCR and NSFR and how this impact changed because of the COVID pandemic. The regression analysis results show similarities and differences between the Liquidity Coverage Ratio and Net Stable Funding Ratio. For the LCR, bank size had a more substantial effect after COVID. The analysis could prove that larger banks increased their short-term liquidity, and GDP growth became more relevant and showed a positive relationship with LCR after the pandemic. For the NSFR, the bank size has a negative impact on both phases. The Z_Score lost its significance after the pandemic.

The similarities between the Liquidity Coverage Ratio and Net Stable Funding Ratio show that the intercept increased after COVID. The results confirm from the first part of the thesis that banks generally held higher liquidity after the pandemic. Also, the cost-income ratio is not significant for both, which means that profitability had no clear impact on either short-term or long-term liquidity. Additionally, the Z_Score was not significant after COVID in either case.

Conversely, the main differences between LCR and NSFR are how bank size and GDP growth influenced the ratios. After COVID, larger banks increased their short-term liquidity but continued reducing their long-term stable funding. The reasons for this can be speculated. Banks might focus more on short-term liquidity to handle sudden market uncertainties. At the same time, they are sure that in the long term, they can handle market uncertainty differently.

A second main result shows that, while the GDP growth had a positive effect on the LCR, it had a negative effect on NSFR. Also, here, the reasons are speculations. However, it seems that if the economy recovers, banks prefer to hold short-term liquidity as a safety buffer rather than maintain long-term stable funding. This goes along with the first results.

While the results provide valuable insights into the impact of COVID on the liquidity of the European banking system, they also have some limitations and improvements that need further research. The chosen predictors are weak because they do not fully explain the effects and changes in the liquidity ratios. The predictors can be defined clearly and separated to deliver more precious outcomes. Also, besides the bank size, profitability, economic conditions, and stability, there might be other essential drivers of liquidity that can be included in further research. Also, choosing

the two Basel liquidity ratios as the primary dependent variables especially brings some weaknesses. These ratios might not reflect all aspects of the liquidity management and the banks' liquidity holdings as they are mainly regulatory measurements. Other variables could be used to analyze the development of the banks' liquidity, for example, by looking directly at the high-liquid assets. This can lead to an even more accurate result. Additionally, the analysis in the thesis shows that COVID primarily drove the increase in liquidity. Nevertheless, further contributors might have to be considered, such as general changes in the government's monetary policy or further events in the financial market that are correlated with COVID. Future research could even more isolate the effect of COVID. How this can be done would be part of the ongoing research.
Besides these weaknesses, the thesis delivers a meaningful contribution to the finance and banking area research, as well as the research on liquidity management and the impact of regulations on the banking market. The thesis provides empirical evidence that the European banks adjusted their liquidity ratios during and after COVID. Also, the differentiation between short-term and long-term liquidity and the different results help to understand the behavior of banks during times of crisis even more. Future research can build on the findings and extend the chosen approach with further predictors described above. Also, future research can extend the analysis beyond 2023 to investigate whether the liquidity ratios are growing further, staying stable or decreasing to the pre-pandemic level. Future research could also extend the geographically used approach, for example, by comparing the here used European market with the banks in the United States. This can help to understand if the results are a global phenomenon or are specific to the European banking system.

7 Appendix A - Figures

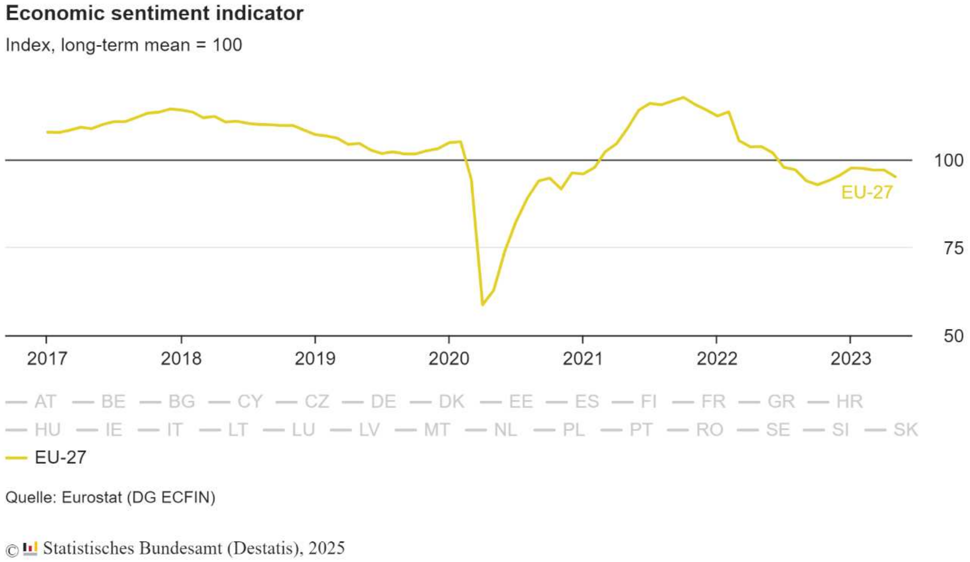

Figure 7 - Economic sentiment indicator (Statistisches Bundesamt, 2023)

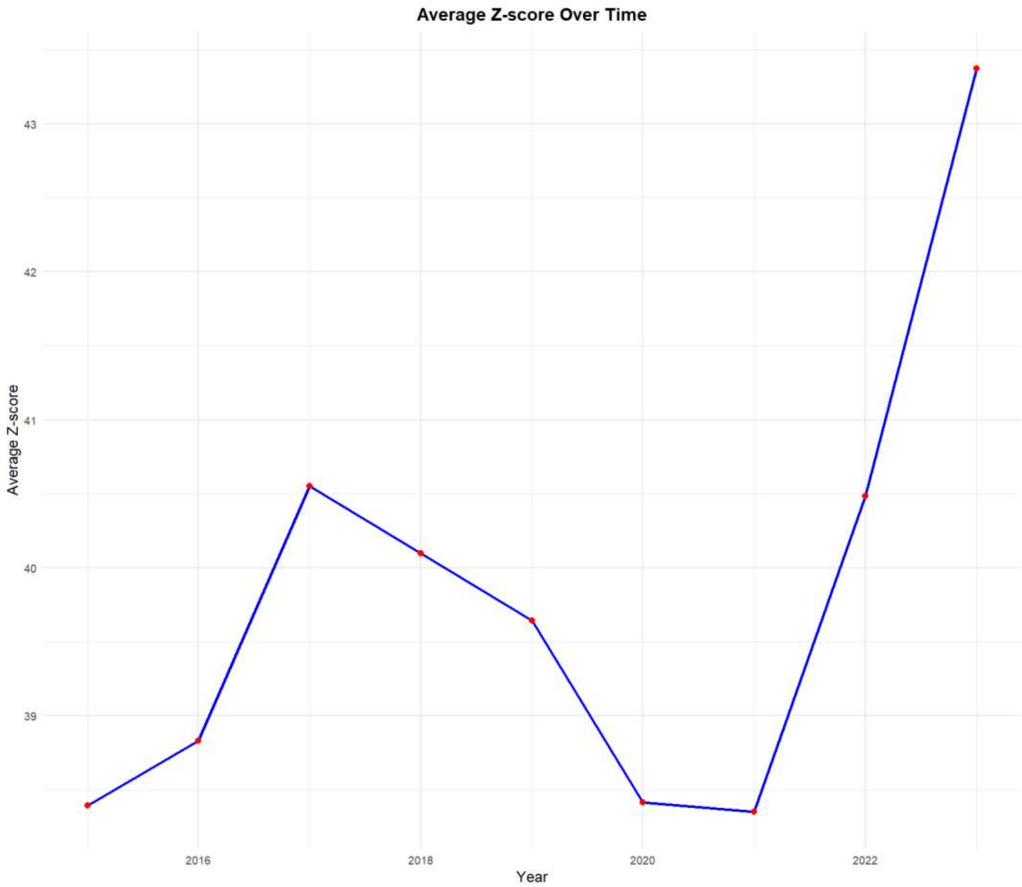

Figure 8 - Z_Score (2015-2023)

8 Appendix B – Tables

Table 13 - Banks, incl. observation years and country

Bank Name	Years Observed	Country
AB SEB bankas	5	Lithuania
ABANCA Corporación Bancaria S.A.	3	Spain
ABN AMRO Bank N.V.	4	Netherlands
Addiko Bank AG	4	Austria
AIB Group plc	9	Ireland
ALPHA SERVICES AND HOLDINGS S.A.	5	Greece
AS LHV Group	7	Estonia
AS SEB Pank	9	Estonia
Banco de Sabadell, S.A.	4	Spain
Banco Santander, S.A.	7	Spain
Barclays Bank Ireland plc	3	Ireland
BANCA MONTE DEI PASCHI DI SIENA S.p.A.	8	Italy
Banca Popolare di Sondrio, Società per Azioni (S.p.A.)	4	Italy
Banco BPM S.p.A.	7	Italy
Banco Comercial Português, S.A.	8	Portugal
Banco de Crédito Social Cooperativo, S.A.	5	Spain
Bank of Cyprus Holdings Public Limited Company	9	Ireland
Bank of Ireland Group plc	9	Ireland
Bankinter, S.A.	6	Spain
Banque Internationale à Luxembourg S.A.	9	Belgium
BAWAG Group AG	5	Austria
Bayern LB	6	Germany
Belfius Banque SA ; Belfius Bank NV ; Belfius Bank SA	9	Belgium
BNG Bank N.V.	9	Netherlands
BNP Paribas S.A.	4	France
BPCE S.A.	4	France
BPER Banca S.p.A.	9	Italy
Bpifrance	1	France
Caixa Geral de Depósitos, S.A.	7	Portugal
CaixaBank, S.A.	6	Spain
Cassa Centrale Banca - Credito Cooperativo Italiano S.p.A.	5	Italy
COMMERZBANK Aktiengesellschaft	2	Germany
Coöperatieve Rabobank U.A.	9	Netherlands
Danske Bank A/S, Finland Branch	4	Finland
de Volksbank N.V.	4	Netherlands

Bank Name	Years Observed	Country
Deutsche Apotheker- und Ärztebank eG	5	Germany
DekaBank Deutsche Girozentrale	3	Germany
Deutsche Bank AG	3	Germany
DZ BANK AG Deutsche Zentral-Genossenschaftsbank	3	Germany
Erste Group Bank AG	9	Austria
Erwerbsgesellschaft der S-Finanzgruppe mbH & Co. KG	3	Germany
Eurobank Ergasias Services and Holdings S.A.	3	Greece
Hamburg Commercial Bank AG	9	Germany
HASPA Finanzholding	7	Germany
HSBC Continental Europe	8	France
Ibercaja Banco, S.A.	7	Spain
ICCREA Banca S.p.A. - Istituto Centrale del Credito Cooperativo	5	Italy
ING Groep N.V.	3	Netherlands
Intesa Sanpaolo S.p.A.	3	Italy
Investeringsmaatschappij Argenta NV ;	9	Belgium
J.P. Morgan SE	3	Germany
KBC Group NV	9	Belgium
Kuntarahoitus Oyj	4	Finland
Kutxabank, S.A.	9	Spain
Landesbank Baden-Württemberg	3	Germany
Landesbank Hessen-Thüringen Girozentrale	6	Germany
Luminor Holding AS	6	Estonia
Münchener Hypothekenbank eG	3	Germany
Nederlandse Waterschapsbank N.V.	9	Netherlands
Norddeutsche Landesbank -Girozentrale-	1	Germany
Nordea Bank Abp	5	Finland
Nova Ljubljanska banka d.d., Ljubljana	6	Slovenia
OP Osuuskunta	8	Finland
Piraeus Financial Holdings S.A.	4	Greece
Raiffeisen Bank International AG	7	Austria
Raiffeisenbankengruppe OÖ Verbund eGen	7	Austria
UBS Europe SE	4	Germany
Unicaja Banco, S.A.	5	Spain
UniCredit S.p.A.	3	Italy
Volkswagen Bank GmbH	4	Germany
Volksbank Wien AG	8	Austria

Bank Name	Years Observed	Country
Wüstenrot Bausparkasse Aktiengesellschaft	3	Germany

Table 14 - GDP Growth Rates per Country

Country	2015	2016	2017	2018	2019	2020	2021	2022	2023
Austria	0.010	0.020	0.023	0.024	0.015	-0.065	0.046	0.048	-0.0070
Belgium	0.020	0.013	0.016	0.018	0.023	-0.054	0.063	0.032	0.0015
Estonia	0.018	0.031	0.056	0.037	0.037	-0.029	0.071	0.001	-0.3000
Finland	0.005	0.028	0.032	0.011	0.012	-0.024	0.032	0.016	-0.0100
France	0.01	0.010	0.025	0.018	0.019	-0.077	0.064	0.025	0.0090
Germany	0.015	0.022	0.027	0.010	0.011	-0.038	0.032	0.018	-0.0030
Greece	-0.002	-0.005	0.011	0.017	0.019	-0.093	0.084	0.056	0.0200
Ireland	0.245	0.018	0.093	0.085	0.053	0.066	0.151	0.094	-0.0032
Italy	0.008	0.013	0.017	0.009	0.005	-0.090	0.070	0.037	0.0090
Lithuania	0.02	0.026	0.043	0.040	0.046	0.001	0.062	0.024	-0.0030
Nether-lands	0.020	0.022	0.029	0.024	0.020	-0.029	0.062	0.043	0.0010
Portugal	0.018	0.020	0.035	0.028	0.027	-0.083	0.057	0.068	0.0230
Slovenia		0.030	0.052	0.044	0.035	-0.041	0.084	0.027	0.021
Spain	0.038	0.030	0.030	0.023	0.020	-0.112	0.064	0.058	0.0025

Table 15 - LCR Statistics (2015-2023)

Year	Mean_LCR	Median_LCR	SD_LCR
2015	1.395444	1.3000	0.3922988
2016	1.551826	1.4000	0.6062691
2017	1.623259	1.4500	0.4414074
2018	1.744083	1.5615	0.5166129
2019	1.859461	1.5845	0.6117149
2020	1.979642	1.9300	0.4831339
2021	2.038708	1.8380	0.6061471
2022	1.899981	1.8190	0.4559348
2023	2.002067	1.8800	0.5582633

Table 16 - NSFR Statistics (2015-2023)

Year	Mean_NSFR	Median_NSFR	SD_NSFR
2015	1.138278	1.153	0.1364598
2016	1.184000	1.190	0.1346078

Year	Mean_NSFR	Median_NSFR	SD_NSFR
2017	1.214041	1.200	0.1241705
2018	1.217917	1.180	0.1361993
2019	1.231211	1.230	0.1430871
2020	1.300579	1.280	0.1497839
2021	1.364703	1.343	0.1491472
2022	1.360435	1.310	0.1745895
2023	1.354300	1.320	0.1624439

Table 17 - ANOVA Tests

Test	Variable	Test_Statistic	P_Value	Interpretation
Shapiro-Wilk Normality Test	LCR	0.89991	0.000000000000001114	Residuals not normally distributed
Shapiro-Wilk Normality Test	NSFR	0.96962	0.000000179900000000	Residuals not normally distributed
Levene's Test for Homogeneity of Variances	LCR	0.28840	0.749600000000000044	Variance is equal across groups.
Levene's Test for Homogeneity of Variances	NSFR	1.52980	0.217799999999999994	Variance is equal across groups.

Table 18 - Naive Regression Model - LCR

Period	Predictor	Estimate	Std. Error	t value	Pr(>|t|)Signif
Pre-COVID	(Intercept)	4.292	0.915	4.689	0.000006***
Post-COVID	(Intercept)	6.475	0.764	8.472	0.000000***
Pre-COVID	Cost_income_ratio	-0.328	0.282	-1.164	0.246347
Post-COVID	Cost_income_ratio	-0.669	0.280	-2.386	0.018459*
Pre-COVID	GDP_growth	-2.166	1.315	-1.647	0.101763
Post-COVID	GDP_growth	1.921	0.757	2.539	0.012290*
Pre-COVID	ln_Size_EUR	-0.096	0.036	-2.668	0.008497**
Post-COVID	ln_Size_EUR	-0.167	0.030	-5.528	0.000000***
Pre-COVID	z_Score	0.001	0.002	0.479	0.632696
Post-COVID	z_Score	0.002	0.001	1.391	0.166425

Table 19 - Naive Regression Model -NSFR

Period	Predictor	Estimate	Std. Error	t value	Pr(>|t|)Signif
Pre-COVID	(Intercept)	1.650	0.230	7.171	0.000000***
Post-COVID	(Intercept)	2.655	0.258	10.291	0.000000***
Pre-COVID	Cost_income_ratio	-0.068	0.071	-0.954	0.341484
Post-COVID	Cost_income_ratio	0.108	0.095	1.142	0.255388
Pre-COVID	GDP_growth	-0.168	0.331	-0.507	0.612717
Post-COVID	GDP_growth	0.412	0.256	1.613	0.109233
Pre-COVID	ln_Size_EUR	-0.017	0.009	-1.917	0.057223
Post-COVID	ln_Size_EUR	-0.051	0.010	-5.031	0.000002***
Pre-COVID	z_Score	0.001	0.000	1.774	0.078124
Post-COVID	z_Score	-0.001	0.000	-2.908	0.004264**

Table 20 - Time Fixed Model - LCR

Period	Predictor	Estimate	Std. Error	t value	Pr(>|t|)Signif
Pre-COVID	(Intercept)	4.009	0.910	4.408	0.000021***
Post-COVID	(Intercept)	6.640	0.753	8.823	0.000000***
Pre-COVID	Cost_income_ratio	-0.393	0.277	-1.420	0.157892
Post-COVID	Cost_income_ratio	-0.502	0.283	-1.772	0.078656
Pre-COVID	GDP_growth	-1.318	1.358	-0.970	0.333506
Post-COVID	GDP_growth	2.956	0.851	3.473	0.000698***
Pre-COVID	factor(Year)2016	0.110	0.173	0.634	0.527197
Pre-COVID	factor(Year)2017	0.195	0.161	1.218	0.225373
Pre-COVID	factor(Year)2018	0.305	0.157	1.945	0.053793
Pre-COVID	factor(Year)2019	0.436	0.154	2.822	0.005464**
Post-COVID	factor(Year)2023	0.224	0.090	2.486	0.014179*
Pre-COVID	ln_Size_EUR	-0.093	0.035	-2.667	0.008539**
Post-COVID	ln_Size_EUR	-0.181	0.030	-6.003	0.000000***
Pre-COVID	z_Score	0.000	0.002	0.234	0.815346
Post-COVID	z_Score	0.001	0.001	1.083	0.280907

Table 21 - Time Fixed model - NSFR

Period	Predictor	Estimate	Std. Error	t value	Pr(>|t|)Signif
Pre-COVID	(Intercept)	1.567	0.232	6.743	0.000000***
Post-COVID	(Intercept)	2.688	0.258	10.416	0.000000***
Pre-COVID	Cost_income_ratio	-0.073	0.071	-1.039	0.300697
Post-COVID	Cost_income_ratio	0.141	0.097	1.452	0.148982

Period	Predictor	Estimate	Std. Error	t value	Pr(>|t|)Signif
Pre-COVID	GDP_growth	0.033	0.347	0.095	0.924378
Post-COVID	GDP_growth	0.615	0.292	2.107	0.036980*
Pre-COVID	factor(Year)2016	0.049	0.044	1.097	0.274383
Pre-COVID	factor(Year)2017	0.075	0.041	1.823	0.070491
Pre-COVID	factor(Year)2018	0.077	0.040	1.931	0.055427
Pre-COVID	factor(Year)2019	0.093	0.039	2.349	0.020201*
Post-COVID	factor(Year)2023	0.044	0.031	1.422	0.157308
Pre-COVID	ln_Size_EUR	-0.017	0.009	-1.865	0.064271
Post-COVID	ln_Size_EUR	-0.054	0.010	-5.229	0.000001***
Pre-COVID	z_Score	0.001	0.000	1.670	0.097111
Post-COVID	z_Score	-0.001	0.000	-3.080	0.002523**

9 Appendix C - Explanation

Liquidity in the Banking Context

Non differentiating between the banking sector and corporates liquidity management focuses on ensuring the ability to meet its payment obligations in full and on time, safeguarding its financial stability and existence. It can be said that liquidity is maintained when the company or bank has sufficient nominal assets (e.g. cash) available or can procure the necessary additional funds. (Guido Eilenberger, 2003, pp. 6–7)In contrast to this, illiquidity occurs when a company or bank fails to secure the required funds to meet its payment obligations, leading to insolvency. Finally, we can define over-liquidity, where available cash and non-interest-bearing bank deposits exceed the required payment needs, poses no financial risk to the company. (Guido Eilenberger, 2003, p. 7)

The liquidity of banks is unique because their business is different from that of cooperatives. The traditional business of banks is to manage short-term deposits while providing long-term loans, called maturity transformation, where they have a need for a careful balance. Their role in the financial system means liquidity issues can affect the overall economy. Managing liquidity is crucial to maintaining trust and stability, especially during sudden withdrawals or market changes. (Greenbaum, Stuart I. & Thakor, Anjan V. & Boot, Arnoud, 2015, p. 287)

Market Liquidity

According to the European Central Bank, market liquidity describes how easily financial assets, for example, bonds or shares of companies, can be bought or sold without causing an impact on their prices. In a very liquid market, transactions are performed very quickly, with minimal costs and disruptions. (ECB, 2007)

There are three key components of a liquid market. The first component describes the difference between the buying and selling prices, which has to be as small as possible. Smaller differences indicate thereby lower transaction costs. The second component is the supply of assets, which measures the ability to perform large trades without significant price decreases; markets with more buyers and sellers are considered more stable. Third, the market's resiliency describes how quickly a market recovers after prices have changed, which is mostly caused by large trades. If a market is resilient, it can quickly return to its original state. Summing up, it can be said that market liquidity ensures that investors, banks and other participants can trade assets efficiently and at reasonable prices. This is mandatory for the confidence and stability in the financial markets. (ECB, 2007)

Funding Liquidity

Beside the market liquidity, it is important to understand funding liquidity in the context of the banking sector. According to (Mathias Drehmann and Kleopatra Nikolaou, 2009, p. 10), funding liquidity can be defined as the ability of a bank to pay its financial obligations on time. If a bank cannot pay what it owes when it is due, it becomes illiquid. Ultimately, this leads to default and losses for its owners and depositors. On the other hand, funding liquidity risks uncertainty about whether a bank will be able to meet its future obligations. It depends on factors like future cash inflows and outflows and the cost of raising funds. Corporate banks rely on central bank money to settle their obligations. This makes the access to funding crucial, especially for large payment systems. (Mathias Drehmann and Kleopatra Nikolaou, 2009, pp. 10–11)

Liquidity in Banks' daily Operations

In the daily operations of banks, liquidity plays a crucial role. Holding an effective amount of liquidity and a required buffer directly impacts the balance sheet and daily cash inflows and outflows. Having a stable liquid daily is called intraday liquidity management. According to a study by Ernst & Young (Gaurav Kohli, Lisa Maus and Abhishek Bhola, 2024) an effective intraday liquidity management ensures that banks can meet their daily payment deadlines without causing any delays, which might affect the whole banking system. It ensures the stability of their customers and counterparties. Besides meeting their obligations, the banks must hold enough liquidity to conduct their daily operations seamlessly. The complexity of controlling the intraday liquidity has increased in recent years. Banks have to process and finalise transactions quickly and repeatedly throughout the day, compared to when they could wait until the end of the day. (Francois Franz, Jai Sooklal and Pete McIntyre, 2022, p. 4) So, they must keep more cash or collateral ready in the short term. Also, customers expect to make payments anytime, so banks cannot plan or delay payments to manage their funds. As a result, banks must continuously investigate their cash flows in real time. They do this across many different systems, often outside normal working hours. In the future, it might be that securities trading accelerates. Banks will face greater pressure to manage their funds even more effectively. (Francois Franz, Jai Sooklal and Pete McIntyre, 2022, p. 4) An effective liquidity management and intraday liquidity comes with a liquidity buffer, which is defined as the stock of liquid assets, such as central bank reserves or high-quality government securities, that can be quickly used to repay obligations. These assets also help manage unexpected changes in cash flows. (Prudential Regulation Authority, 2020, p. 1) The liquidity coverage ratio tries to guarantee such a liquidity buffer.

Individual Liquidity Guidance

While this thesis mainly focuses on the liquidity rules given by the Basel Accords, which will be explained in detail in the following paragraphs, it is helpful for the overall understanding to look at further guidelines. In contrast to the liquidity coverage ratio, which was introduced from 2015 to 2019, the United Kingdom has already introduced the Individual Liquidity Guidance (ILG) from 2010 to 2015, as investigated in a recent paper by Dennis Reinhardt et al. (Dennis Reinhardt *et al.*, 2023)The ILG's setup is identical to the LCR's, which will be discussed in the next chapter.

In their paper, they investigate how the ILG impacts the cross-border lending of banks in the UK and how quickly banks react to adjustments in the liquidity rules, which is also an essential aspect in the analysis that follows in this thesis. They could prove that banks increase their liquid assets, especially at a high rate, just before regulatory requirements come into effect and are reduced afterwards again. Considering this, the analysis in this thesis builds up in the way that it looks at the liquidity ratio over a more extended period after a fixed introduction and does not consider the period before the introduction of the Basel 3 accords.

The paper's main result shows that banks try to hold their liquidity constant and higher than the requirements. Additionally, they could find evidence that banks with larger shares can react more easily to higher liquidity requirements. Also, ILG and LCR are not identical. Their results give a first indicator of the upcoming results in this thesis, as similar control variables will be used to explain the changes of the LCR. (Dennis Reinhardt *et al.*, 2023)

Transition Phase

The Basel Committee introduced the requirements with a phased approach to ensure banks could adapt them without disrupting any lending. The Liquidity Coverage Ratio was tested from 2011 onwards and implemented in 2015. The Net Stable Funding Ratio began the same year and was implemented starting 2018. The process included monitoring and adjustments to address any issues. (Basel Committee on Banking Supervision, 2010, p. 9)

Monitoring incentives

According to Carl Olsson, 2022, pp. 369–371 ratios have to be reported completely, accurately and timely. Also, the format has to follow the correct approach. The expectations of the Basel committee were published in 2013 as “Principles for Risk data aggregation and risk reporting,” which contains fourteen principles that must be fulfilled. A detailed explanation of these principles will not be included in this thesis.

Additional Monitoring Metrics for Liquidity

Additional monitoring metrics were implemented to ensure the correct reporting of the liquidity rules. These metrics were first introduced as the Additional Liquidity Monitoring Metrics (ALMM) and later developed as the Additional Monitoring Metrics for Liquidity Reporting (AMM), which were introduced at the end of 2018. (Dr. Alexander Hick, Bernhard Kretschmar, Daniel Schulz, Franziska Händel, 2017) According to the Deutsche Bundesbank, the following monitoring metrics need to be reported: Maturity ladder, Concentration of funding by counterparty, Concentration of funding by product type, Prices for various lengths of funding, Roll-over of funding and the Concentration of counterbalancing capacity by issuer. (Deutsche Bundesbank Eurosystem, no date) The EU implemented these metrics through its regulations to handle regional needs. The key updates include tracking cash inflows, outflows, and reserves. The reports also monitor refinancing costs and daily cash flows to detect risks early. These measures ensure that banks maintain strong liquidity and comply with the liquidity ratios, especially in the combination of the stress tests included in the liquidity coverage ratio. (Dr. Alexander Hick, Bernhard Kretschmar, Daniel Schulz, Franziska Händel, 2017)

Finalising post-crisis reforms (Basel IV)

In December 2017, the Basel Committee on Banking Supervision accepted extensive adjustments on Basel III, commonly called Basel IV. The term Basel IV is nevertheless not officially used (Gregor Krämer, 2020). According to Gabler Bank-Lexicon, the changes include updates to the credit risk measurement methods, adjustments in internal models for risk portfolios, and a new credit valuation. Also, new leverage ratio requirements are introduced for globally important banks. Last, the risk-weighted assets are adjusted (Gregor Krämer, 2020). The updated frameworks do not impact the scope of the analyses of this thesis and therefore are not taken further into account.

Net interest margin

The cost income ratio as a measurement of efficiency in the banking sector includes several factors of costs and is partly questioned in the current literature. A paper by Burger and Moormann, for example, investigates the validity of the cost income ratio. (Burger, Moormann and Sottocornola, 2008). Their paper argues that the ratio is unsuitable for efficiency analysis as country-specific interest margins and labour costs influence it. They suggest using analyses that allow an evaluation more independent of these factors.

Since more detailed methods such as the SFA and DEA mentioned in the previous section would exceed the scope of the master's thesis, the net interest margin (NIM) is used as an additional independent variable in this thesis.

According to Greenbaum et.al (Greenbaum, Stuart I. & Thakor, Anjan V. & Boot, Arnoud, 2015, pp. 292–293) The net interest margin is defined as the difference between yield on assets (investment returns) and the interest costs of the liabilities (Investment expenses), divided by the bank's total assets.

$$Net\ interest\ Margin = \frac{Investment\ Returns - Investement\ Expenses}{Total\ Assets}$$

The analysis of the annual reports has shown that the banks seem to calculate the NIM on different approaches, for example, by dividing by the average earning assets.

Pillar 2 - Supervisory Review Process

Pillar 2 of Basel II focuses on ensuring banks maintain adequate capital to support all risks, including those not fully captured under Pillar 1. A newspaper article by Bozena Guljija summarised the key parts as follows. (Bozena Gulija, 2022)

The second pillar of the Basel II accords shall respond to the increasing complexity of the bank operations and ensure that risks, for example, due to globalization and technologies, are reviewed. It is, therefore, an addition to the capital requirements from Pillar 1, which were described in the previous section.

The main component of pillar 2 is the newly introduced Supervisory Review Process (SRP), which includes two parts. First is the Internal Capital Adequacy Assessment Process (ICAAP), and second is the Internal Liquidity Adequacy Assessment Process (ILAAP). (FMA, 2024) Both were designed to evaluate the capital and liquidity needs of the banks based on their risk profiles. Supervisors then review these assessments. They do this via the SRP. By this approach, it can be assured that risk, capital requirements, and liquidity requirements are aligned within the banks. Another part of pillar 2 is an intervention mechanism, which allows authorities to react if the capital level of the banks is starting to be inadequate. Risk coverage is expanded to include further risks, like strategic, interest rate, and climate risks. (Bozena Gulija, 2022)

Pillar 3—Enhanced Disclosure/Market Discipline

The committee explained the relevance and importance of transparency and disclosure. Therefore, Pillar 3 introduced requirements for banks to inform the public and regulators about their risk profiles, capital adequacy, and risk management practices. This should help stakeholders make more informed decisions and hold banks accountable for their activities.

Leverage Ratio

Prior to the financial crisis, banks built up high leverage in their balance sheet and, as well as off-balance, used the positive effects of a leverage effect. To counteract the increased risk that this creates, a leverage ratio was introduced with the Basel 3. The ratio is defined as follows: The Bank's regulatory core capital is defined as the numerator, which is divided by its total exposure in the denominator. (Deutsche Bundesbank, no date)

$$Leverage\ Ratio = \frac{Core\ Capital}{Exposure\ Measure}$$ [1]

The denominator includes both on-balance-sheet and off-balance-sheet items. (Deutsche Bundesbank, no date) The calculation has to be done on a quarterly basis and reported with the Pillar 3 disclosure requirements. (Carl Olsson, 2022, p. 242)A low ratio indicates relatively high leverage compared to the core capital. The valuation of the balance sheet positions is based on the bank's accounting standards. This ratio has to be above 3%, which is set on the low end of the scale and can be increased by national regulators. The goal is to reduce the overall leverage in the institutions. (Pascal Jessberger, 2013)

Difficulties especially come up in the process of calculating the exposures. Different values from different sources have to be summed up, including derivatives, off-balance sheet items, further components, and, of course, on-balance sheet items. All these components are included with differently calculated values and do not necessarily match with their actual value. (Carl Olsson, 2022, pp. 239–240) The exact determination and the consequences might be of interest for further research.

According to Olsson, leverage, in general, is important for the banking system. (Carl Olsson, 2022, p. 236). By using higher leverage, banks can increase their earnings and their return on equity, as well as their return on assets. It works as banks work differently than manufacturing companies. Nevertheless, this behaviour raises credit and liquidity risks. Using the return of assets in a calculated z-score, which will be explained later, these aspects are included in the overall analysis of this thesis.

The effect of the leverage ratio is part of the research in recent papers, like in a 2018 published research by Allahrakha et al. (Meraj Allahrakha, Jill Cetina and Benjamin Munyan, 2018). In their paper, they investigate how the leverage ratio affects the repo market. They want to find out if the ratio influences large banks to shift from using safer assets like, for example, agency mortgage-backed securities (MBS) to riskier assets. For example, collateral equity. This change may increase funding risks and lead to a transition from regulated banks to less regulated banks. Their results indeed show this connection can lead banks to undertake riskier activities and create opportunities.

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[1] Carl Olsson (2022, p. 239).

Disclosure requirements

While with the implementation of Basel 2, disclosure requirements were already introduced, they were reviewed with Basel 3 and published in an updated framework. The Basel committee published the following updates in 2018 (Basel Committee on Banking Supervision, 2018)

The updated Pillar 3 disclosure requirements enhanced the practices compared to Basel II. The new requirements focus on providing more detailed information about banks' risk profiles and capital adequacy. One of the key updates is the enhanced risk disclosure, which includes more detailed information on various risks like credit risk and operational risk, as well as an already explained leverage ratio. The enhanced disclosure requirements should allow stakeholders to better understand the risks that banks face. An important addition to Basel 2 is the requirement for banks to disclose information about asset liabilities. This information is crucial for assessing the availability of a bank's assets to creditors in the event of insolvency. Furthermore, the updated requirements include new disclosure requirements regarding capital distribution constraints. Using all these aspects, the enhancements shall lead to greater transparency and a more comprehensive approach to risk management.

Available Stable Funding (ASF)

The available stable funding, ASF, is used for the ratio's numerator. The ASF is defined as the sum of available items providing a stable funding source. The evaluation of the funding rate is hereby calculated based on stress conditions according to different factors. (Carl Olsson, 2022, pp. 230–231) The range of these factors starts from 100% for very stable funds to 0% for very unstable liabilities.

The Committee of Baking Supervision (Basel Committee on Banking Supervision, 2014, pp. 4–5) Classifies the factors in five levels as follows:

For regulatory capital, without Tier 2 instruments with a maturity below 1 year, and for further liabilities over one year, 100% are considered. For stable deposits without maturity and deposits provided by retail customers below one year maturity, 95% are considered. For less table deposits without maturity provided by retail customers, the factor is calculated as 90%. Fundings by non financial corporates with less than one year maturity, operational deposits and other fundings with a maturity between six months and one year, which are not part of the first three categories 50%

is used as a factor and for all other liabilities and equity and as well for liability without a mentioned maturity 0% can be used in the calculation of the ASF.
Using these factors, banks calculate the ASF by multiplying the factor with the value of the liabilities in the category and summing up the sums. The total sum amounts to the ASF.

Required Stable Funding (RSF)
According to the officially published standard by the Bank for International Settlements, the required stable funding ratio is calculated using the bank's assets and off-balance sheet assets. (*LCR Liquidity Coverage Ratio LCR30 High-quality liquid assets* 2019). It shall evaluate the stability of the bank's funding in contrast to the liquidity characteristics and the maturity profiles of the assets, in addition to the bank's off-balance-sheet activities.
It was introduced to ensure that the banks maintain sufficient stable funding to withstand a year-long period of financial stress, by which we can see the opposite to the liquidity coverage ratio, which was introduced to guarantee short-term liquidity, which was described above. The factors which are included reflect the likelihood that an asset will need stable funding. They consider its residual maturity and encumbrance status. (*LCR Liquidity Coverage Ratio LCR30 High-quality liquid assets* 2019)
The Basel Committee explain the percentage requirements as follows. The liabilities that are valued at 50% RSF include funding from non-financial corporate customers, with maturities between six months and one year, as well as operational deposits. Liabilities with a 0% RSF factor include maturities under six months, such as short-term funding from central banks and financial institutions. High-quality liquid assets, such as central bank reserves, have very low RSF factors while less liquid or encumbered assets, such as non-performing loans or fixed assets, receive a 100% RSF factor. (*LCR Liquidity Coverage Ratio LCR30 High-quality liquid assets* 2019)
The RSF also includes off-balance-sheet exposures. This comprehensive approach ensures banks account for potential liquidity outflows while maintaining a stable funding profile to meet regulatory standards.

10 Appendix D - Tools

Microsoft Word & Excel

Word was used for writing, structuring, and formatting the document, including organising chapters and inserting citations.
Excel was used for data analysis and the preparation of the financial data.

Grammarly

Grammarly was used to check the grammar and spelling.

RStudio

RStudio was used for the data analysis, to create the statistical models (Regression models, ANOVA, etc.), and to visualise the results and trends.

ChatGPT

ChatGPT was used to correct and improve the R-code.

Citavi

Citavi was used to organise references and citations.

S&P Capital IQ

S&P Capital IQ was used for data research.

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